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ABSTRACT

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

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1 Introduction

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.

It is often suggested that more trusting may help promote economic prosperity, especially in less developed economies. The existing literature typically measures trust as how trusting people are in response to opinion surveys, and relates trusting level to economic performance measures.[1] In this paper, we argue that a policy that encourages buyer trusting may lead to *less trust* in equilibrium because it attracts more strategic sellers to enter and may induce more cheating behavior from strategic sellers after entry. Intuitively, blind trusting by unsophisticated buyers invites dishonest sellers, which certainly does not increase the trust level. However, we show both theoretically and empirically that even under rational expectation, more trusting can be associated with less trust and slower market expansion.

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

To organize our thoughts, we build a simple rational expectation model to understand how trusting-promoting policies trigger the reactions of buyers and sellers and thus affect the equilibrium trust and market size. In particular, we consider a widely-used trusting-promoting policy: buyer protection, whereby a market maker can promise buyers a "money back guarantee" should they be cheated by sellers. In our model, 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 het-

[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). These types of opinion surveys are widely used to analyze the effects of trust on economic performance.

erogeneous in entry cost and production cost. If a seller delivers a low-quality product and the buyer reports it to the platform, the platform can reimburse the buyer and penalize the seller.

Under certain assumptions, we show that buyer protection can reduce equilibrium trust. The idea is as follows. More generous buyer protection increases buyers' willingness to buy, and in response sellers raise prices. The resulting increase in expected profit motivates differential entry between honest and strategic sellers. Disproportionally more strategic sellers will be attracted to the market because their returns from entry increase more than those of honest sellers. Furthermore, as prices increase, returns from cheating are larger so strategic sellers may be induced to engage in more cheating. Consequently, buyer protection can reduce the equilibrium level of trust. As more generous buyer protection leads to lower trust, the probability of completing a transaction may be lower because rational buyers expect the negative effects of buyer protection on seller trustworthiness. If the effect on the completion rate is sufficiently strong, the market size may even decrease as more buyer protection is offered.

With these predictions in mind, we investigate the effects of buyer protection in early e-commerce in China. As a developing country with a legacy of a planning economy, China has long suffered from weak laws and frequent fraud in the market. When Eachnet (an eBay equivalent in China) introduced e-commerce into China in 1999, it encountered an even worse trading environment than offline markets due to the anonymity of online transactions. In its early days, Eachnet experimented with multiple tools to boost trust, including buyer protection, seller feedback scores, and a warning system, which offers us an excellent opportunity to link these policies to transaction outcomes and market development. China's weak legal environment also forces buyers to rely on market mechanisms to develop and enforce trust. Because reputation building is gradual and dependent on market size, buyer protection is often considered a powerful tool to encourage buyers to trust an early market and therefore promote market development.[2]

We examine a large transaction dataset from Eachnet.com. While feedback scores had been in place since the beginning of our sample (June 2001), Eachnet did not adopt buyer protection until October 2001. Its first protection policy offered buyers up to 3000 RMB per transaction, a coverage close to universal, as 98% of completed transactions were under 3000 RMB at that time. Eleven months later, Eachnet lowered the upper limit of reimbursement to 1000 RMB

[2] A well-accepted view is that reputation building is an important factor for trust. Trust level in a society will be higher if individuals, firms, and organizations are motivated to build reputation over time. Reputable sellers are more reluctant to cut corners because a damaged reputation implies less business and profit in the future (Klein and Leffler, 1981; Shapiro, 1982). But reputation building takes time and requires repeated interactions and other institutional supports (e.g., good monitoring). In the model, we focus on the effect of trusting-promoting policies, instead of reputation building, on the equilibrium level of trust. In the empirical analysis, we will examine how buyer protection affects the role of seller reputation in market performance.

and introduced a deductible of 100 RMB per transaction. These variations allow us to identify the effect of buyer protection policies from the overall growth of Eachnet. Between the two buyer protection regimes, Eachnet started to issue warnings to traders who were found guilty upon their trading partner's complaint to Eachnet. Warnings could result in a complete ban on trading on Eachnet, effectively the only online trading platform in China at that time. We observe seller feedback and seller warning outcomes on the same transaction and will use both to infer seller trustworthiness.

Data analysis yields two findings: First, when buyer protection is more generous, sellers are less likely to receive positive feedback and more likely to receive an Eachnet warning about a completed transaction. The negative effect of buyer protection on seller's positive feedback is found to be greater for high-value goods than for low-value goods, and more buyer protection is linked to lower completion rate and higher price for completed listings. These results provide supporting evidence for our theoretical model. The second finding relates buyer protection to market size, which is measured by the number of listings and sellers in each product category. A greater coverage of buyer protection is found to be correlated with a reduction in market size, suggesting that the negative effect of buyer protection on completion rate (due to buyer anticipation of lower trust) dominates its original encouragement of buyer trusting.

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

Our paper is also related to a growing literature on e-commerce. Most empirical papers in this literature focus on online reputation, for example the effect of seller reputation on completion rate and transaction price on eBay (as reviewed in Bajari and Hortascu, 2004 and Dellarocus, 2003), the dynamics of seller reputation in eBay (Cabral and Hortacsu, 2010), the experimental studies on reputation building (Bohnet and Huck, 2004), and ways to improve the feedback system (Bolton, Katok and Ockenfels, 2004). We are aware of only one paper on buyer protection (Roberts, 2011), which uses transaction data from a US website for tractors and farm machinery to study whether buyer protection affects the influence of seller reputation on price and probability of sale. Roberts concludes that buyer protection does not substitute for reputation and attributes this ineffectiveness to either buyer insensitivity to small reputation differences or buyer skepticism of the protection program. In contrast, we investigate the effect of buyer protection on seller behavior and market size, both of which are not readily measured in Roberts (2011). Our theoretical and empirical results help us understand why a policy that targets buyer trusting can reduce trust and why trust is difficult to build in emerging markets.

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

2 Institutional Background

2.1 Eachnet

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

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

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

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

2.2 Buyer Protection and Seller Warning

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

In our subsequent analysis, we will focus on three regimes of buyer protection: 1) regime 0: zero coverage prior to October 2001; 2) regime 1: generous coverage from October 2001 to August 2002; and 3) regime 2: partial coverage in and after September 2002. Table 1 describes the two buyer protection policies by transaction price. The second policy, especially the variation in coverage of different values, is essential for us to identify the effect of buyer protection. In comparison, the first policy is close to full protection for almost all transactions; thus, its effect is not easily identifiable from the rapid market growth of Eachnet in the sample period.

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

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

3 Theoretical Model

3.1 Basic Model

Consider a market (a trading platform such as Eachnet) where there are two types of sellers: honest and strategic. Only a seller knows his own type. In the population, the proportion of honest sellers is α in $(0, 1)$. An honest seller always honors his promise by delivering a high quality product. Cheating means delivering a poor quality product. Producing poor quality costs c_0 to any seller. The cost of producing a high quality product is also c_0 for an honest seller, so he never cheats.[3]

A strategic seller honors his promise only when it is in his interest. We assume that the cost of a strategic seller to produce a high quality product, denoted by c, is uniformly distributed on $(c_0, C + c_0)$. 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

[3] We can relax this assumption by supposing that an honest seller incurs a cost of $\bar{c} > c_0$ from producing a high quality, and $\bar{c} < c + n$ where n is the expected penalty from producing a low quality product. Then honest sellers will always produce high quality products.

probability τ. For simplicity, we assume that buyers never misreport. Upon receiving the buyer complaint, Eachnet imposes a penalty $A \geq 0$ on the misbehaving seller. Thus, a strategic seller will cheat if and only if his cost of producing a high quality product c is greater than the expected penalty $n = \tau A$. We assume $n > c_0$ so that strategic sellers with the lowest cost will not cheat.

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

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

Consider the following game:

- In stage 1, buyers and sellers decide whether to enter the market. To focus on seller entry, we assume that buyers have zero entry cost and that the entry cost of sellers, denoted by k, is uniformly distributed on $(0, K)$. Before entry, each seller knows his own type and entry cost, but strategic sellers do not know their costs of high quality products.[4]

- 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.[5] The seller in each match announces a price p.[6]

- In stage 3, the buyer in a match decides whether to buy. If the buyer decides to buy, she pays the seller-announced price and the seller decides whether to produce a high or poor quality product. If the seller is of the strategic type and chooses to cheat, the buyer in this match reports to Eachnet with probability τ. Upon receiving the buyer complaint, Eachnet

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

[5] Our model can be extended to the case when one seller is matched with multiple buyers who compete in an auction to determine price. See Footnote 8 for details.

[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.

imposes a punishment A on the cheating seller and compensates the buyer's reimbursement claim equal to a fixed fraction w of the transaction price p, so that the total compensation is $I = wp$.

An equilibrium must satisfy three conditions: each seller makes optimal entry, pricing and quality decisions in order to maximize his (expected) net profit; each buyer makes an optimal purchasing decision; and each buyer's belief in the probability of receiving a low quality product reflects the actual probability of cheating in the marketplace. 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. As shown in the Appendix, the equilibrium level of trust and the equilibrium price are jointly determined by the following two equations:

$$p(\gamma, V, e, \tau, w, c_0) = \frac{c_0}{2} + \frac{\gamma(V+e)}{2(1-(1-\gamma)\tau w)}, \tag{1}$$

$$\frac{1}{1-\gamma} = \frac{\alpha[(n-c_0) - \frac{(n-c_0)^2}{2C}]}{(1-\alpha)(1-\frac{n-c_0}{C})(p-n+\frac{(n-c_0)^2}{2C})} + \frac{1}{(1-\alpha)(1-\frac{n-c_0}{C})}. \tag{2}$$

Equation (1) is derived from sellers' optimal pricing decision, given buyers' trusting level γ. We focus on a pooling equilibrium, where strategic sellers mimic honest sellers in pricing; otherwise, price alone will reveal the strategic type.[7] In such a pooling equilibrium, honest sellers set an optimal monopoly price, and strategic sellers fellow suit.[8] Plotting Equation (1) in a graph of p against γ, Figure 1 shows p as an increasing function of γ. This is because the more

[7] If strategic sellers price differently from honest sellers, they must set a lower price as buyers expect more cheating from them. However, setting a lower price implies less profit and therefore cannot be an optimal strategy for strategic sellers.

[8] We mentioned earlier that our model could be extended to the case in which a seller is matched with multiple buyers. In such a case, buyers will compete in an ascending English auction. With identical and independent private valuation, this is equivalent to the second price auction in which buyers will bid their true valuation (as in a proxy bid). Let b be a bid for a buyer with a valuation of v for a high quality product. Then her expected valuation of a unknown quality product is $\gamma v + (1-\gamma)\tau w b$. Equalizing this with b gives $b = \gamma v/[1-(1-\gamma)\tau w]$. Note that by standard auction theory, the buyer will set an optimal reserve price precisely as given by Equation (1), which is independent of the number of buyers. Thus, with multiple buyers, the realized price for a completed transaction is either the price given by Equation (1) (when only one bid is above the reserve price), or $\gamma v_{(2)}[1-(1-\gamma)\tau w]$ (when two or more bids are above the reserve price), where $v_{(2)}$ is the second highest valuation. Taking the conditional expectation over $v_{(2)}$, we can see that the expected price in the latter case has the same properties as the price equation given by Equation (1), in particular, the monotonic relationship with regard to w.

a buyer believes in high quality delivery (higher γ), the more she is willing to pay for the item, which motivates the seller to charge a higher price. Moreover, the more buyer protection there is (higher w), the greater the buyer's willingness to pay (conditional on γ), which encourages higher prices.

Equation (2) is derived from the equilibrium condition of rational expectation that, upon taking into account sellers' entry decisions, buyer belief in receiving a high quality product must be equal to the overall probability of sellers delivering high quality products. Plotting Equation (2) in Figure 1, we can see that p is a downward sloping curve of γ. This is because in rational expectation buyer belief in the probability of getting high quality depends on the ratio of honest and strategic sellers entering the market, and on the probability of strategic sellers honoring their promises (which is independent of price). Higher prices motivate both types of sellers to enter the market, but the effect is greater on strategic sellers. This can be seen from the following equation, which gives the relative ratio of honest to strategic sellers in the market:

$$R = \frac{\alpha(p - c_0)}{(1-\alpha)[p - n + \frac{(n-c_0)^2}{2C}]}. \tag{3}$$

Since $n - (n - c_0)^2/(2C) > c_0$ (otherwise $n > c_0 + 2C$ then strategic sellers never cheat), R decreases in p. Intuitively, the expected cost of a strategic seller (a weighted combination of the production cost of a high quality product and the expected penalty cost from producing a low quality product) is greater than that of an honest seller. Thus, as the transaction price increases, the return from entry increases faster for strategic sellers than for honest sellers. Consequently, proportionally more strategic sellers will be attracted to the market following a price increase.

The intersection of Equations (1) and (2) in Figure 1 determines a unique equilibrium of the model. At the equilibrium, we have the following comparative statics (all proofs are contained in the Appendix):

Proposition 1 *The equilibrium level of trust(γ) decreases with buyer protection (w) and buyer's average value of high quality product (V), but increases with penalty on cheating behavior (A) and proportion of honest seller in the population (α).*

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

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

Proposition 2 *The negative effect of buyer protection (w) on the equilibrium level of trust is more prominent for high-value products.*

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

Proposition 3 *Equilibrium price (p) increases with buyer protection(w), cheating punishment(A), buyer's average value of high quality products (V) and the proportion of honest sellers in the population (α).*

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

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

$$CR = \frac{V+e}{4e} - \frac{c_0(1-(1-\gamma)\tau w)}{4e\gamma} \tag{4}$$

Proposition 4 *The completion rate (CR) increases with cheating penalty (A) and the proportion of honest sellers in the population (α).*

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

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

$$MS = \frac{CR}{K}\{p - c_0 - (1-\alpha)[(n-c_0) - \frac{(n-c_0)^2}{2C})]\} \tag{5}$$

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

Proposition 5 *Under certain conditions, the market size is decreasing in the degree of buyer protection (w).*

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

3.2 Extensions

To make the model as simple as possible, we assume that strategic sellers all face the same expected penalty n. This implies that the probability of a strategic seller cheating is constant at $1 - \frac{n-c_0}{C}$ as long as the price is above n (otherwise strategic sellers would never cheat). Thus, the effects of buyer protection are driven solely from the differential entry between honest and strategic sellers.

The model can be easily extended to allow changes in cheating behavior of strategic sellers. Suppose the expected penalty n a strategic seller faces if she cheats is uniformly distributed on $[n_1, n_2]$ where $c_0 < n_1 < n_2 < c_0 + C$, where the randomness of n comes from either uncertainty about buyer reporting τ (different buyers may have different propensities of reporting cheating behavior) or randomness in reputation loss from the penalty A imposed by the marketplace (the same penalty may impose different costs to different sellers). For simplicity, suppose strategic sellers know about their expected penalty n at the same time when they know their production cost of producing high quality products. Then a strategic seller will cheat if $n < c$ and $n < p$. It is easy to show that the probability of a strategic seller cheating is $(1 - \frac{n_1+n_2-2c_0}{2C}) * \frac{p-n_1}{n_2-n_1}$

when $n_1 < p < n_2$. It can be shown that all the main results of the basic model still hold in this extension.

In this extension, buyer protection does not only trigger differential entry between honest and strategic sellers, but also affect the cheating probability of strategic sellers after entry. Intuitively, as prices increase with stronger buyer protection, some strategic sellers who would not cheat at lower prices (when their expected penalty is higher than the price) will be attempted to cheat at higher prices (when the price exceeds their expected penalty). Simply put, higher prices mean greater returns from cheating, thus stronger incentives to cheat. Therefore, with stronger buyer protection, the proportion of strategic sellers engaging in cheating is larger. This additional effect reinforces our result that stronger buyer protection leads to less trust. And with more reduction in the equilibrium level of trust, stronger buyer protection is more likely to lead to slower market expansion.[9]

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

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

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

4 Data

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

For each product listing, we know whether it resulted in a completed transaction, where online completion means a buyer either agreed to pay the buy-it-now price or won the auction by offering a final price above the minimum price or the secret reservation price if such reservation existed. For each completed transaction, we observe four categories of information: 1) seller demographics including gender, age, income, occupation and region (if reported);[10] 2) seller history such as registration date, cumulative feedback score before the transaction, plus seller feedback and the Eachnet warning on this transaction if there is any; 3) buyer demographics (same as that of the seller)[11]; and 4) information on the listed product, pricing method (auction vs. fixed price), auction format, the transaction price and transaction closing time. Eachnet did not give us data on the exact text/picture description of an item or its bidding history.

For incomplete listings, we observe seller demographics and product information, but not buyer or transaction information.[12] One data challenge is that our raw data do not report the seller's cumulative feedback score before a listing if that listing was incomplete. However, since we know the seller's complete listing history, we first sort the data by seller id and listing time (detailed to second), and then impute the seller's feedback score as the same from his most recent completed transaction. Because we lack the seller's buying history, which could also contribute to seller feedback score, this imputation may introduce an upward or downward bias, especially if the seller's last completed transaction happened long time ago. We create a dummy equal to one if the time lag from the last completed transaction to the studied listing is more than 30 days, and control for this variable in all transaction-specific regressions. That being said, most of our key regressions are either conditional on completed transactions or based on a simple count of unique listings, and therefore do not need imputed seller scores.

[10] 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%).

[11] 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.

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

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

We focus on the sample period from June 1, 2001 to March 31, 2003 because the feedback score system was formally introduced in May 2001 and there is little information about trader behavior before the score system. We then rule out duplicates[13] as well as outliers that have transaction price, reserve price or listing price over 100,000 RMB. If a listing sells multiple units of a product and that listing leads to multiple transactions (with either different buyers or the same buyer at different close times), they appear as multiple records in the raw data. We keep them as separate transactions, but our count of unique listings only uses seller and listing information. This is why the number of records could exceed the number of listings in our summary statistics.

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

Dividing the sample by three regimes of buyer protection, Table 2 presents regime-specific summary on market volume, listing attributes, completion rate, seller reputation at the time of listing, and feedback/warning outcomes. Over time, the number of listings grew rapidly. This trend is likely driven by faster growth in relatively low value items, as all prices used in listings – minimum, buy-it-now, or reservation price when it is available – tend to drop from regime 0 to regime 2. The big difference in various price measures between means and medians suggests that

[13]In rare cases (less than 0.5% of the data), we observe multiple records that contain the same buyer id, same seller id, same product id, same listing time, and same closing time. One possibility is that the buyer purchased multiple units from the same listing but Eachnet counted it as multiple transactions. We collapse such duplicate records into one. In very few cases, these duplicate records report different feedback on the seller. When we collapse them, we define the seller feedback as positive/negative/neutral for this transaction if the average feedback across the duplicate records is positive/negative/zero. Including duplicated records in the final sample does not affect our regression results.

price distribution is positively skewed. Over time, sellers became more likely to sell newer items, list multiple items under the same listing, post pictures, quote buy-it-now prices, and become less likely to use bold fonts or auction.[14] As expected, seller scores increased over time, partly due to organic growth of reputation, partly due to the fact that reputable sellers are more likely to stay active in the market. Throughout the paper, we group missing, zero, and negative score as "fishy" scores. Completion rate increases significantly from 35.44% in regime 0 to 55.22% in regime 1 and then remains stable at 54.42% in regime 2.

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

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

In terms of seller feedback, sellers were more likely to receive any feedback in regimes 1 and 2 than in regime 0. Of all completed transactions, fewer and fewer sellers received negative feedback over time. The percentage of sellers receiving positive feedback increased sharply from 32.68% in regime 0 to 56.95% in regime 1, and then dropped slightly to 53.32% in regime 2. Figure 3 plots the monthly percentage of sellers receiving positive feedback throughout the 22 months of our analysis sample. A similar graph for the percentage of negative seller feedback is provided in Figure 4. These two percentages do not add up to one, because we count missing and neutral feedback as the residual group. Both figures show a strong and non-linear trend throughout the whole market, which highlights the importance of controlling for overall market growth (and other factors such as seller reputation and listing attributes). In both figures, we plot the data for four ranges of final price: below 100, between 100 and 1100, between 1100 and 3000, and over 3000. As the theory predicts, higher-value items are more likely to receive negative feedback and less likely to receive positive feedback.

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

Figure 5 plots the percentage of sellers receiving Eachnet warnings by month. Consistent with seller feedback, seller warning rate is higher for higher-value items. Its difference across price ranges increased to some extent after Eachnet revised its buyer protection policy in September 2002.

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

5 Empirical Tests

This section first correlates buyer protection with transaction-specific outcomes such as seller feedback, seller warning, completion rate, and final price if the listing was completed. We then continue to examine whether buyer protection has affected market size. In the last subsection, we investigate whether the identified effects of buyer protection are driven by within- or across-seller variations.

5.1 Seller Feedback and Seller Warning

We are mostly interested in the role of buyer protection in promoting trust. As stated in Proposition 1, buyer protection (w) reduces equilibrium trust (γ) in our theoretical model.

In testing this prediction, the biggest challenge is that we do not directly observe whether a seller has cheated in a transaction. What we observe are feedback and the Eachnet warning that a seller receives on a specific transaction. Assuming a buyer report is authentic, the probability of a seller receiving positive feedback is a product of the seller not cheating[15] and the buyer submitting positive feedback conditional on being treated well. Similarly, the probability of a seller receiving negative feedback is a product of the seller cheating and the buyer submitting negative feedback conditional on being cheated, and the probability of a seller receiving Eachnet warning is a product of seller cheating and buyer complaining to Eachnet conditional on being cheated. All four factors – seller behavior and the three buyer reporting probabilities – could change in response to buyer protection. Although we observe four outcomes for the same transaction,

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

namely positive feedback, negative feedback, no/neutral feedback[16] and Eachnet warning, the first three must add up to one and therefore we only have three degrees of freedom, which is not enough to identify the effect of buyer protection on the above four factors.

One way to overcome this identification problem is assuming that buyer probability to submit positive feedback (conditional on good seller behavior) does not change with the buyer protection. This assumption is likely to hold because both buyer protection and Eachnet warning target misbehavior rather than good behavior. Nevertheless, it could be violated if buyers feel less need to contribute any feedback after the Eachnet introduced buyer protection and/or warning. As long as this change is universal across the market, it is absorbed in year-month fixed effects. To the extent that a buyer reporting positive feedback conditional on good seller behavior may be sensitive to the price she pays (or the value of the item), this can be addressed by controlling for price (or item value) as long as the reporting dependence on price/value does not change over time. In fact, because buyer protection changes non-monotonically over time, we can even allow the impact of price/value to follow different linear trends for different price/values over time. With all these controls, the identification assumption we really need is that the probability of buyer reporting positive feedback conditional on good seller behavior does not change differentially by the degree of buyer protection. We believe this is a reasonable assumption because buyer protection is irrelevant to the buyer if the seller behaves and the buyer report is truthful.[17]

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

The second identification challenge is that buyer protection coverage depends on transaction price but price is endogenously determined in equilibrium. Our solution is constructing a predicted price for each listing and using the predicted price to calculate expected buyer protection. In particular, for an item listed on day i in a finely-defined (level-four) product category, we look at all the previous listings in the same category that were completed in the closest five days

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

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

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

before day i. The average transaction price of these previous listings is defined as the predicted price for this listing. Of all the 1,570,334 records in our sample, we are able to define valid predicted price for 1,223,991 of them (77.9%). Appendix Table reproduces Table 2 conditional on having a valid predicted price. By definition, regime 0 has less history to calculate predicted price and therefore is less likely to have valid predicted price. Otherwise, most patterns in the sub-sample with predicted price are similar to the full sample.

5.1.1 Econometric Specification

With the above-stated assumptions, we estimate the following equation:

$$Y_{istk}{=}\theta_w w_i{+}\theta_p \hat{p}_i{+}\theta_s S_i{+}C_i\theta_c{+}X_i\theta_x{+}\theta_b B_i{+}\theta_t{\cdot}\mathrm{t}{\cdot}\hat{p}_i{+}\alpha_t{+}\alpha_k{+}\epsilon_{it}. \tag{6}$$

where i denotes a listing, t denotes year-month, s denotes seller identity, k denotes market as defined by level-two category code.

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

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

We also control for $\hat{p}$ directly because our model predicts that seller trustworthiness should depend on item value in the eyes of buyers. To the extent that buyer reporting probability differs by product value, it is also captured in the coefficient of $\hat{p}$. To test whether w has a bigger impact on higher-valued items, one version of the specification reports coefficients of w for $\hat{p}$ below and above 500 RMB separately.[20]

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

[20] In another specification, we estimate different coefficients of w for $\hat{p}$ below 100, between 100 and 1100, and above 1100 RMB. Results are qualitatively similar.

S denotes seller attributes such as the seller's Eachnet score at the time of listing, gender, region, and Eachnet age since registration.[21] Following the existing literature, we treat seller score as an indicator of seller reputation. Loss of reputation is one form of penalty for cheating sellers (A in the model), but it is difficult to judge whether the penalty is greater when a seller score drops from 100 to 99 than from 10 to 9. One can also interpret seller score as a proxy that signals (to buyers) the probability of the seller being an honest type, which corresponds to the population share of honest sellers (α) in the model. Because of this ambiguity, we refer to the coefficient of seller score as reputation effects. In some specifications, we include an interaction of seller score and a dummy of after-buyer-protection, to examine whether the reputation effect varies with the introduction of buyer protection. Similarly, we sometimes include an interaction of seller score and a dummy of after-Eachnet-warning.

C denotes competition from similar items on the Eachnet. To construct C, we first calculate the number of listings in the same finest category (up to four-level category code) in seven days before the listing date of the studied listing, and then divide it by the total number of view count on these listings (measured in thousands).[22] View count attempts to measure market demand for that fine category. In the model, we normalize buyer's outside option as zero. Empirically, C is a proxy for buyer's outside option.

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

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

Lastly, we control for $t \cdot \hat{p}$ to allow items of different values to follow different trends in feedback and warning outcomes. We aslo control for year-month fixed effects, α_t, and product category fixed effects, α_k.

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

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

5.1.2 Regression Results

Table 3 presents regression results regarding whether a seller receives positive feedback on a single transaction. Columns 1-3 use final price to calculate degree of buyer protection, Columns 4-6 use buy-it-now price, and Columns 7-9 use predicted price. Under each measure of buyer protection, we report three specifications: the first reports a single coefficient of w; the second reports one coefficient of w for $\hat{p} \leq 500$ and one for $\hat{p} > 500$; the third specification allows seller score variables to interact with one dummy of after-buyer-protection and one dummy of after-Eachnet-warning. We report all results from a linear probability model, controlling for product category fixed effects (~180), seller region fixed effects (at the city level, ~24 as we consolidate small regions as one default group), buyer region fixed effects (~24), and year-month fixed effects (~22). Every specification also controls for $\hat{p}$ and $t \cdot \hat{p}$, where t is the number of calendar months since the start of our analysis sample (June 2001). Results are robust if we do not include $t \cdot \hat{p}$ or if we add a quadratic term of $\hat{p}$.

In all specifications, we find that buyer protection has a significant, negative effect on the likelihood of a seller receiving positive feedback. Under the assumption that buyer reporting is authentic and the probability of reporting positive feedback conditional on good seller behavior does not change with buyer protection, this result confirms Proposition 1 that sellers are less trustworthy when Eachnet offers greater buyer protection. In particular, the coefficient of w in Column 7 indicates that a change from no protection to full protection reduces the likelihood of seller positive feedback by 4.7 percentage points. This is a large effect as compared with the sample average of seller positive feedback (54%). Consistent with Proposition 2, we also find a greater, negative effect of buyer protection on higher-value items. According to Column 8, the coefficient of w for $\hat{p} > 500$ is -0.079, nearly 80% higher than that for $\hat{p} \leq 500$ (-0.044).

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

Table 4 reports regression results of equation (8) on seller negative feedback and seller warning. Recall that buyer protection may generate changes in both seller trustworthiness and buyer reporting; thus, the prediction on seller negative feedback and seller warning are more uncertain. As we did for seller positive feedback, we report three sets of results for seller negative feedback, with buyer protection calculated by final price, buy-it-now price and predicted price respectively. For each measure of buyer protection, the second specification interacts seller score variables with a dummy of after-buyer-protection and a dummy of after-Eachnet-warning. These interactions cannot be identified for seller warning outcome, as Eachnet adopted a warning system after buyer protection. Hence we only report three columns of seller warning results.

Most of Table 4 is consistent with seller behavior inferred from Table 3: greater buyer protection is related to more seller negative feedback and more seller warning; higher log (seller score) is related to less negative feedback and less warning; having a missing/negative/zero seller score is related to more negative feedback and more warning. The only exception is the negative coefficient of w on seller negative feedback, where w is calculated by predicted price.[23] One possible explanation is that mistreated buyers tend to complain to the Eachnet warning system instead of reporting negative feedback.

5.2 Completion Rate and Final Price

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

$$1_{completed,istk} = (\alpha_{2s}) + \theta_{2w} w_i + \theta_{2p}\hat{p}_i + \theta_{2s} S_i + C_i\theta_{2c} + X_i\theta_{2x} + \theta_{2t}\cdot t\cdot \hat{p}_i + \alpha_{2t} + \alpha_{2k} + \epsilon_{2it}, \quad (7)$$

$$log(p_{istk}) = \theta_{3w} w_i + \theta_{3s} S_i + C_i\theta_{3c} + X_i\theta_{3x} + \alpha_{3t} + \alpha_{3k} + \epsilon_{3it}. \quad (8)$$

Right hand side variables follow Equation (8) with three exceptions: first, we use only predicted price to calculate buyer protection, because either final or buy-it-now price can be interpreted as transaction outcomes;[24] second, we do not include buyer attributes as they are not available for incomplete transactions and are jointly determined with price if they are available; third, we do not control for predicted price in the price regression because predicted price by definition aims to predict transaction price for that listing.

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

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

Table 5 presents linear regressions results for both completion rate and log final price. Because one listing may list multiple units of the same item and lead to multiple transactions, our unit of analysis is per unique listing for completion rate and per transaction for log price. We count a listing as completed if it leads to at least one complete transaction.[25] The price regression clusters error by listing id. In the even-numbered columns, we interact seller score variables with the after-buyer-protection and after-Eachnet-warning dummies.

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

Consistent with the previous e-commerce literature, the log of positive seller score increases completion rate and log price, while having a negative, zero or missing score reduces probability of sale. Surprisingly, sellers with a negative, zero or missing score also enjoy a price premium, compared to those with a reputation score of one. A possible interpretation is that sellers with inferior records target high-price items even though the chance of completing the transaction is small. As shown in Tables 3 and 4, "fishy" sellers do get more negative feedback, less positive feedback, and more warnings if their listings are completed.

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

5.3 Market Size

Within the Eachnet data, we define each two-level category code (k) as a separate market. Among a total of 180 categories, 116 have at least one listing completed by the first month of our

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

analysis sample (June 2001). In light of this, our study of market size focuses on the development of these 116 markets since July 2001, while taking each market as of June 2001 as the initial condition. In particular, we estimate:

$$N_{kt} = \theta_w w(\bar{p}_{k0}) + \theta_t \cdot t \cdot \bar{p}_{k0} + \alpha_t + \alpha_k + \epsilon_{it} \tag{9}$$

where k denotes product category, t denotes year-month, $\bar{p}_{k0}$ denotes market k's average transaction price in June 2001, and $w(\bar{p}_{k0})$ is the degree of buyer protection one would expect category k to have over time assuming the average value of potential listings remain at $\bar{p}_{k0}$. The above specification does not control for $\bar{p}_{k0}$ directly because it is absorbed in category fixed effects (α_k). The key coefficient, θ_w, is identified from the overall market growth (controlled by year-month fixed effects α_t) and a differential time trend by category's average value ($t \cdot \bar{p}_{k0}$), because buyer protection policy differs by item values and changes non-monotonically over time.

Recall that our model makes an ambiguous prediction on the effect of buyer protection on market size: on the one hand, protection from the platform makes buyers more willing to transact at a given price and a given belief of seller trustworthiness; on the other hand, if buyer protection reduces equilibrium trust, rational buyers anticipate this negative effect and adjust their belief accordingly. When the latter dominates the former, buyer protection reduces completion rate and market size. Table 5 illustrates the negative effect of buyer protection on completion rate, so we expect buyer protection to reduce market size. Table 6 confirms this prediction, whether we measure market size N_{kt} by the total number of listings, the total number of listed units, or the total number of unique sellers. The second panel of Table 6 expands the market size regressions to the full sample, while defining $\bar{p}_{k0}$ as of the first month that category k appeared in our analysis sample. Results are similar between the two panels, suggesting that the market shrinking effect of buyer protection is not driven by the addition of new markets on Eachnet.

5.4 Cross- and Within-seller Variations

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

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

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

To empirically examine cross- or within-seller variations, we rerun the positive feedback regression with seller fixed effects, and report the new results in the first two columns of Table 7. To save space, we only report the regression where buyer protection is calculated by predicted price.[26] Comparing Table 7 with Table 3, we find that the coefficients of buyer protection are of the same sign and similar significance after we control for seller fixed effects, but their magnitudes drop roughly 25% for both high- and low-value items. This suggests that the worsened seller trustworthiness in response to buyer protection is driven by both cross- and within-seller variations, but the within-seller variations are of greater importance.[27]

The last four columns of Table 7 report completion rate and price regressions with seller fixed effects. Within the same seller, greater buyer protection is still found to be associated with a significantly lower probability of sale and higher final price. This suggests that buyers anticipate the same seller to become more strategic in face of greater buyer protection, and therefore are more reluctant to complete the transaction.

Results with and without seller fixed effects reveal some interesting patterns regarding seller reputation. Without seller fixed effects, Tables 3, 4 and 5 show that seller reputation predicted better seller feedback and higher probability of sale in regime 0, but these indicative effects were weakened after Eachnet introduced buyer protection and warning. When we add seller fixed effects (Table 7), the coefficient of log seller score is no longer positive for seller positive feedback, and its interactions with after-buyer-protection dummy and after-warning dummy remain negative. Similarly, the coefficient of log seller score in the completion regression, though

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

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

still positive, is much smaller and sometimes even insignificant if the regression includes seller fixed effects. These coefficient estimates suggest that the positive correlations between better seller reputation, better seller behavior, and higher completion rate are mostly driven by cross-seller variations. While reputation may help distinguish good and bad sellers cross-sectionally, having a better reputation does not necessarily motivate the same seller to behave better. More puzzling is the effect of reputation variables on final price. Regardless of whether or not we control for seller fixed effects, log seller score does not link with higher price until Eachnet introduced buyer protection or warning. One possible explanation is that buyer protection motivates the same seller to behave more strategically in terms of pushing for higher transaction price but not to behave as well as before in delivery and other services.

So far we have demonstrated some distinctions between cross- and within-seller variations. How do they contribute to market-wide changes in response to buyer protection?

At the market-month level, we rerun equation (9), but instead of using market size as the dependent variable, we focus on seller composition as measured by (1) fraction of new sellers in category k at month t where new is defined as appearing in our whole analysis sample of Eachnet for less than 30 days as of the time of listing, (2) fraction of sellers that are new to category k at month t but have existed on Eachnet for more than 30 days, (3) log of average seller score for all unique listings that appeared in category k at month t, (4) fraction of sellers with missing seller scores at the time of listing, and (5) fraction of sellers with missing, negative, and zero seller scores at the time of listing. The results reported in Table 8 suggest that greater buyer protection in a category does not change the fraction of new sellers in that category but attracts more existing sellers to enter that category. The log of average seller score is found to increase with buyer protection, while the fraction of sellers with missing, negative and zero seller scores decreases with buyer protection. These findings are consistent with each other, because existing sellers typically have better reputation than new sellers.

The last three columns of Table 8 associate buyer protection of a category with the average seller feedback and warning outcomes from that category. It turns out that greater buyer protection is associated with no significant improvement in seller positive feedback, no significant change in Eachnet warnings, and somewhat less negative feedback.

These market-wide changes can be explained by a combination of cross- and within-seller variations. On one hand, greater buyer protection in a category attracts existing sellers to enter this category, which increases the average seller reputation in that category. Cross-sectionally, better seller reputation should imply better seller behavior. On the other hand, buyer protection has motivated the same sellers to behave more strategically and therefore counteract the former effect.

Above all, empirical results suggest that, although the negative effects of buyer protection on seller trustworthiness are related to both cross- and within-seller variations, they are more likely driven by within-seller variations. Market-wide, greater buyer protection leads to more existing sellers entering into a category and on average better seller reputation in that category. However, buyer protection still hinders market expansion because the same sellers become more strategic in response to buyer protection and buyers expect less seller trustworthiness accordingly.

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 policy that targets buyer trusting can have unintended consequences and eventually hurt equilibrium trust and market development. We demonstrate this possibility in a simple model and find confirming evidence from the early age of Eachnet.com. Our results imply that promoting market size in under-developed economies requires more than trying to increase the trusting level in the society. Building institutions (especially a well functioning legal system) to ensure seller trustworthiness is fundamental.

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

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7 Appendix: Solution to the Model

We solve the model by backward induction. In stage 3, a strategic seller will cheat if $c \geq n = \tau A$ and $n < p$. With sufficient high expected penalty ($n \geq C + c_0$), all strategic sellers will not cheat; we assume $n < C + c_0$ to avoid this trivial case. For the same reason, we focus on the equilibrium in which $p > n$.[28] When $n < C + c_0$, the proportion of cheating among strategic sellers is $1 - \frac{n-c_0}{C}$.

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

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

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

$$\pi^H = (p - c_0)[\frac{V + e - \bar{v}}{2e}]$$

The optimal price has an inner solution when $V - 3e < c_0 < V + e$:

$$p(\gamma, V, e, \tau, w, c_0) = \frac{c_0}{2} + \frac{\gamma(V+e)}{2(1-(1-\gamma)\tau w)}$$

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

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

For all solutions, it is easy to see that $\frac{\partial p}{\partial V} > 0$, $\frac{\partial p}{\partial \gamma} > 0$, $\frac{\partial p}{\partial \tau} > 0$, and $\frac{\partial p}{\partial w} > 0$. In what follows, we mainly focus on the more interesting case–inner solution, and turn to the other case when it is necessary. At the optimal price, the probability of sale is $CR = \frac{V+e-\bar{v}}{2e} = \frac{V+e}{4e} - \frac{c_0(1-(1-\gamma)\tau w)}{4e\gamma}$ and the expected profit of an honest seller is $\pi^H = (p - c_0)CR$.

Now we turn to strategic sellers. Given p, if $p \geq C + c_0 > n$ or $C + c_0 > p \geq n$, 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:

$$\pi^S = E_c\{[(p-c)\frac{n-c_0}{C} + (p-n)(1-\frac{n-c_0}{C})][\frac{V+e-\bar{v}}{2e}]\} = [p - n + \frac{(n-c_0)^2}{2C}]CR$$

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

If $C + c_0 > n \geq p$, a strategic seller will not provide low quality because the expected penalty n is greater than the price; he will provide high quality as long as his production cost c is below p. Thus, before knowing c, his expected profit will be

$$\pi^{SH} = E_c\{(p-c)[\frac{V+e-\bar{v}}{2e}]\} = \frac{(p-c_0)CR}{2}$$

and the strategic seller will not enter unless $\pi^{SH} \geq k$. In other words, when $C + c_0 > n \geq p$, all the strategic traders who choose to enter the market provide high quality products. Consistently, buyers hold the belief of $\gamma = 1$ which leads to $p = (V + e + c_0)/2$. This case is less interesting, so we rule it out by assuming $V + e + c_0 > 2n$.

In stage 1, a seller makes his entry decision by comparing the expected profit π^S(or π^H) and his entry cost k. Strategic sellers will enter the market with probability $\rho = \frac{\pi^S}{K}$. The entry probability of honest sellers is $\phi = \frac{\pi^H}{K}$. To ensure $\rho \leq 1$ and $\phi \leq 1$, we assume that $K \geq \frac{(V+e-c_0)^2}{8e}$. Accordingly, rational buyers should believe that the probability of getting a high quality product is $\gamma = \frac{\alpha\phi+(1-\alpha)\rho\frac{n-c_0}{C}}{\alpha\phi+(1-\alpha)\rho}$. Rearranging terms, we get

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

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 $p = (V + e + c_0)/2$ is greater than the endpoint of curve (2) at $p = n - \frac{(n-c_0)^2}{2C}$ by our assumption $V + e + c_0 > 2n$.

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

Proof of Proposition 2:

we aim to prove $\frac{\partial^2\gamma}{\partial V \partial w} > 0$. We first define the relative ratio of honest seller to strategic seller: $R = \frac{\alpha(p-c_0)}{(1-\alpha)[p-n-\frac{(n-c_0)^2}{2C}]}$. It can be easily shown that R is decreasing with p and increasing with n. Then buyers' belief curve (2) can be written as a function of R:

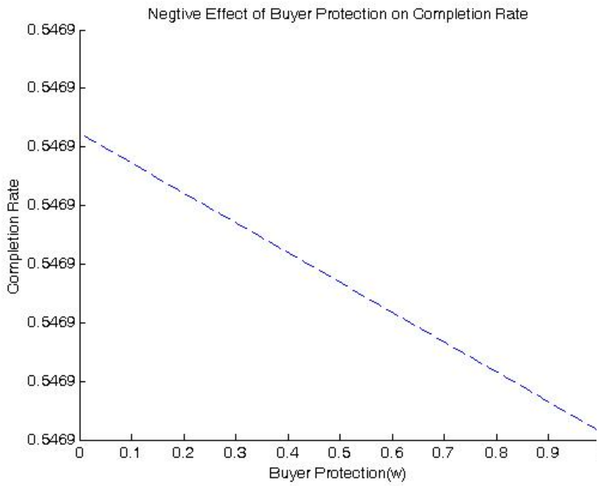
$$\gamma = \frac{\alpha\phi + (1-\alpha)\rho\frac{n-c_0}{C}}{\alpha\phi + (1-\alpha)\rho} = 1 - \frac{1-\frac{\hat{n}}{C}}{1+R} \tag{10}$$

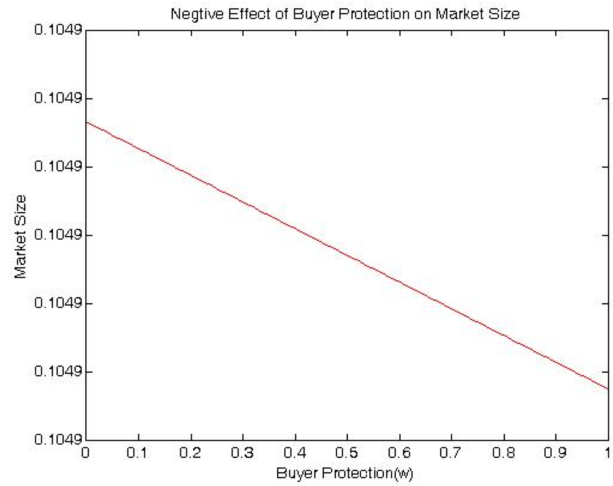
where $\hat{n} = n - c_0$. From the above equation (10), we may get $\frac{\partial\gamma}{\partial V} = (1-\frac{\hat{n}}{C})\frac{1}{(1+R)^2}\frac{\partial R}{\partial p}\frac{\partial p}{\partial V}$. Then,

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

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

Simulation of Proposition 5:





Simulation results help us find some possible parameters[29] with which buyer protection(w) may negatively affect completion rate as well as market size. The below two figures prove our arguments.

[29]We set up parameters as follows: $\alpha = 0.55, V = 2, e = 1.6, c_0 = 0.1, \tau = 0.4, C = 4, K = 5, A = 6.8$.

Figure 1: Equilibrium and Comparative Statics: Baseline Model

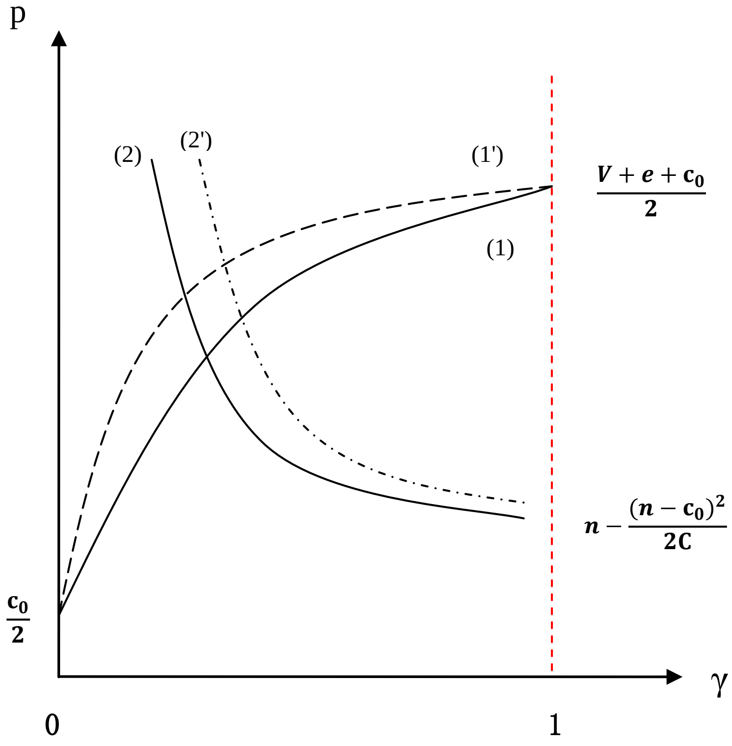


Figure 2: Comparative Statics for the Mean of Buyer Valuation (V)

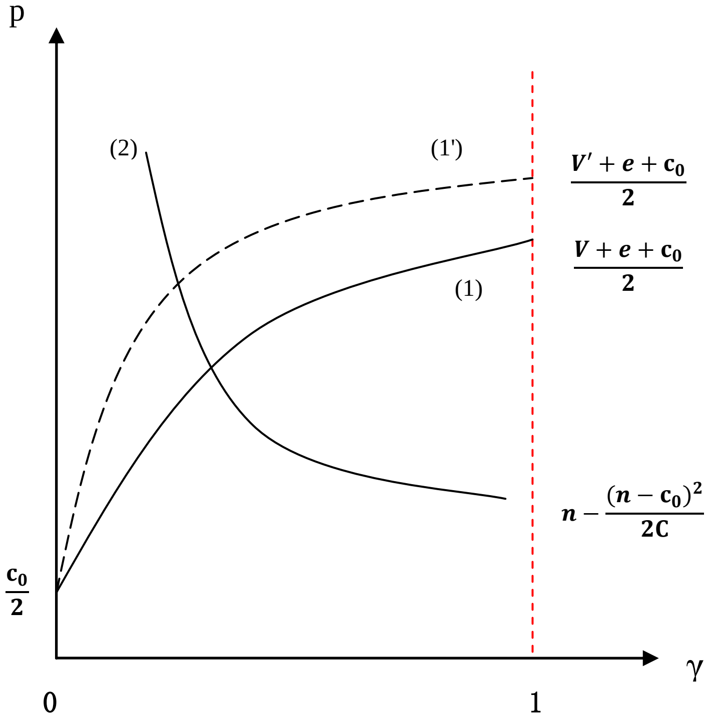
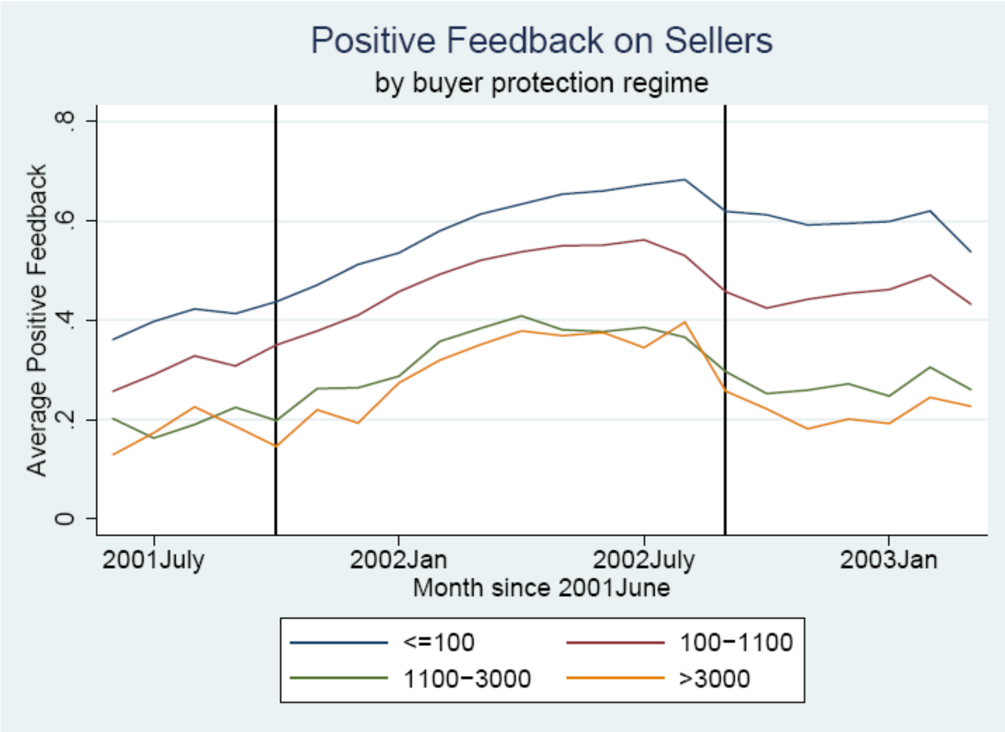
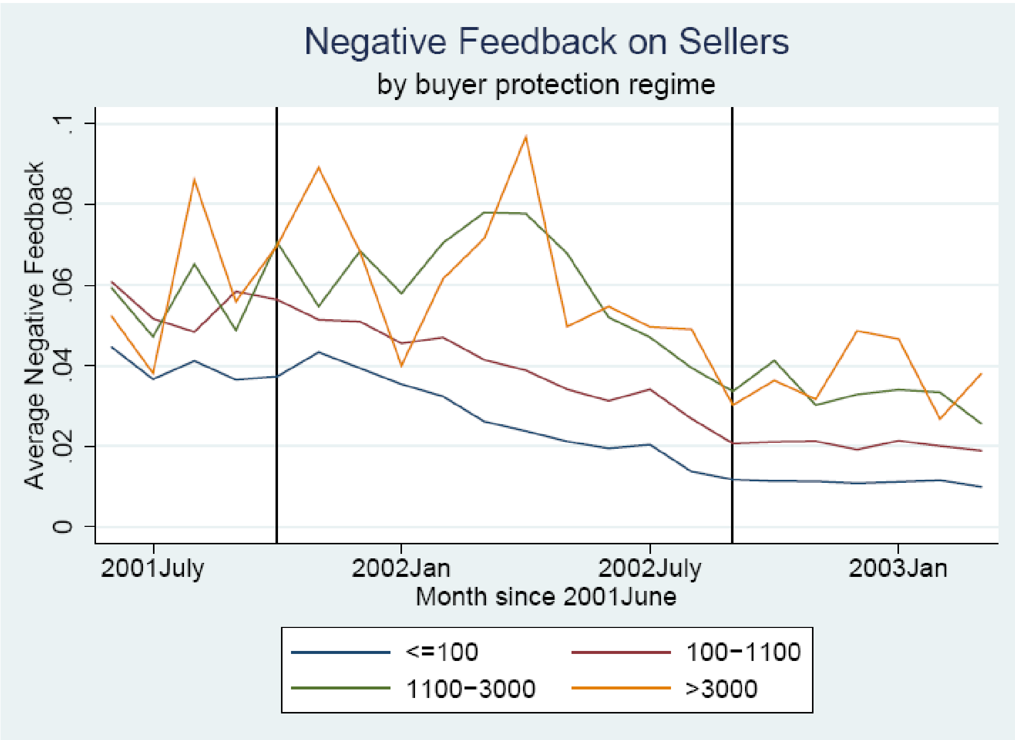


Figure 3: Seller Positive Feedback by Buyer Protection Regime



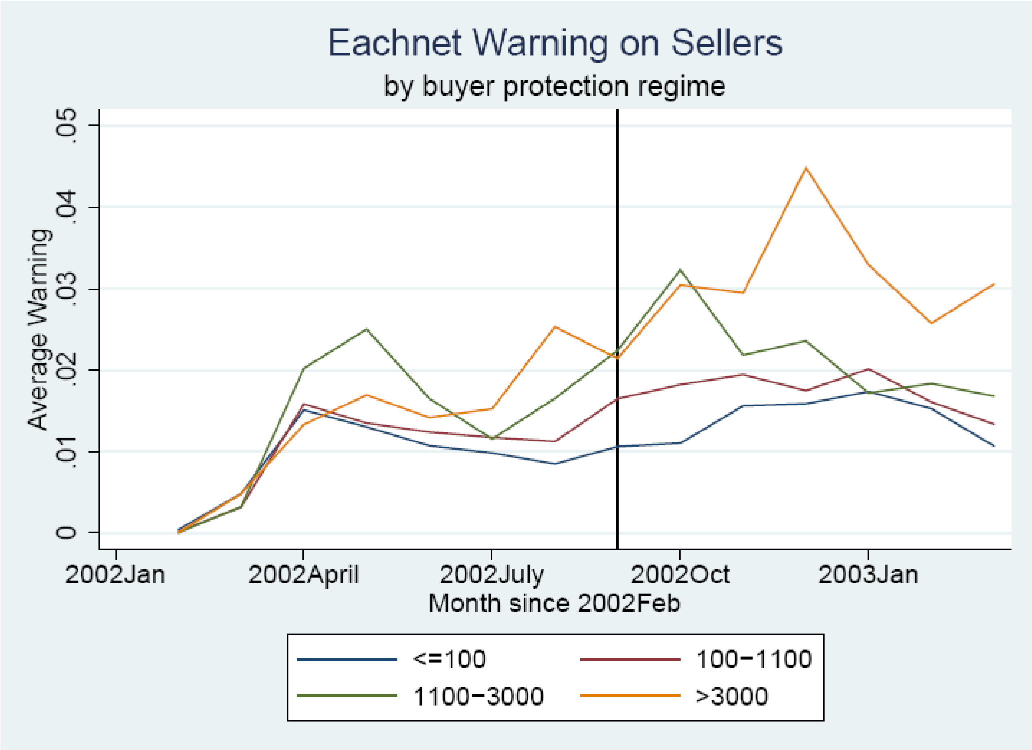
Note: The two vertical lines correspond to the first month of Regime 1 (October 2001) and the first month of Regime 2 (September 2002).

Figure 4: Seller Negative Feedback by Buyer Protection Regime



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

Figure 5: Seller Warning by Buyer Protection Regime



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

Table 1: Percentage of the Price Covered by Buyer Protection

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

Table 2: Summary Statistics

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

Table 2 Continued: Summary Statistics

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

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

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

	Dependent Variable = 1 if Seller Receives Positive Feedback								
Price used to calculate buyer protection	Final Price			Buy-it-now Price			Predicted Price		
% price protected by Eachnet	-0.082**		-0.083**	-0.080**		-0.081**	-0.047**		-0.048**
	(0.003)		(0.003)	(0.003)		(0.003)	(0.004)		(0.004)
% of protection | p<=500		-0.068**			-0.035**			-0.044**	
		(0.003)			(0.004)			(0.004)	
% of protection | p>500		-0.121**			-0.102**			-0.079**	
		(0.003)			(0.005)			(0.005)	
price (in thousand)	-0.007**	-0.004**	-0.005**	-0.012**	-0.004*	-0.010**	-0.042**	-0.036**	-0.035**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
log (seller score at time of listing)	-0.005**	-0.005**	0.032**	-0.005**	-0.006**	0.033**	-0.006**	-0.006**	0.035**
	0.000	0.000	(0.003)	0.000	0.000	(0.004)	0.000	0.000	(0.004)
=1 if seller score is missing or <=0	-0.081**	-0.080**	-0.068**	-0.076**	-0.081**	-0.071**	-0.080**	-0.080**	-0.063**
	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)	(0.010)	(0.003)	(0.003)	(0.010)
after protection * log(seller score)			-0.025**			-0.028**			-0.024**
			(0.003)			(0.004)			(0.005)
after protection * seller score missing or <=0			-0.029**			-0.024+			-0.025+
			(0.009)			(0.013)			(0.013)
after warning * log(seller score)			-0.013**			-0.011**			-0.017**
			(0.002)			(0.002)			(0.002)
after warning * seller score missing or <=0			0.025**			0.027**			0.014
			(0.007)			(0.009)			(0.009)
Observations	969,337	969,337	969,337	789,908	783,566	789,908	783,566	783,566	783,566
R-squared	0.16	0.161	0.161	0.159	0.161	0.16	0.16	0.161	0.161

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

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

	Seller Receives Negative Feedback						Seller Receives Eachnet Warning		
Price used to calculate buyer protection	Final price		Buy-it-now price		predicted price		Final price	Buy-it-now price	predicted price
% price protected by Eachnet	0.003**	0.003**	0.004**	0.005**	-0.004**	-0.004**	0.002**	0.005**	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
price (in thousand)	0.001*	0.001	0.003**	0.003**	0.011**	0.011**	-0.002**	-0.002**	-0.004**
	0.000	0.000	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log (seller score at time of listing)	-0.003**	-0.007**	-0.002**	-0.005**	-0.003**	-0.007**	-0.002**	-0.002**	-0.002**
	0.000	(0.001)	0.000	(0.001)	0.000	(0.002)	0.000	0.000	0.000
=1 if seller score is missing or <=0	0.011**	0.007*	0.010**	0.012*	0.010**	0.001	0.011**	0.010**	0.012**
	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)
after protection * log(seller score)		0.000		-0.001		0.001			
		(0.001)		(0.002)		(0.002)			
after protection * seller score missing or <=0		0.008+		0.004		0.015*			
		(0.005)		(0.006)		(0.007)			
after warning * log(seller score)		0.005**		0.004**		0.003**			
		(0.001)		(0.001)		(0.001)			
after warning * seller score missing or <=0		-0.006+		-0.006		-0.006			
		(0.003)		(0.004)		(0.005)			
Observations	969,337	969,337	789,908	789,908	783,566	783,566	890,288	741,868	739,398
R-squared	0.015	0.015	0.014	0.014	0.015	0.015	0.011	0.01	0.011

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

Table 5: The Effect of Buyer Protection on Completion Rate and Price

	Completed		log (final price)	
% predicted price protected by Eachnet	-0.004+	-0.006*	0.561**	0.574**
	(0.003)	(0.003)	(0.026)	(0.026)
Predicted price (in thousand)	0.442**	0.058		
	(0.070)	(0.071)		
log (seller score at time of listing)	0.019**	0.046**	0.075**	-0.130**
	(0.000)	(0.003)	(0.003)	(0.017)
=1 if seller score is missing or <=0	-0.422**	-0.195**	0.304**	-0.085+
	(0.001)	(0.008)	(0.018)	(0.049)
after protection * log(seller score)		-0.013**		0.095**
		(0.004)		(0.018)
after protection * seller score missing or <=0		-0.085**		0.298**
		(0.010)		(0.057)
after warning * log(seller score)		-0.017**		0.114**
		(0.002)		(0.007)
after warning * seller score missing or <=0		-0.166**		0.089*
		(0.006)		(0.036)
Observations	985,265	985,265	783,566	783,566
R-squared	0.28	0.282	0.44	0.44

Note: A listing is defined completed if the listing leads to at least one completed transaction. Predicted price refers to the average final price of similar items (in the same level-four category) completed in the last seven days before the study listing. All regressions control for year-month fixed effects, day of week fixed effects, product category fixed effects, seller's Eachnet age,, seller region fixed effects, seller gender, listing attributes, predicted price, # of months since June 2001*predicted price, competition measured by # of similar listings in last 7 days per thousand view count, and a dummy =1 if the competition measure is over 50. Robust standard errors in parentheses. In price regressions, errors are clustered by unique listing id. +p<10%,*p<5%,**p<1%.

Table 6: The Effect of Buyer Protection on Market Size

	log (total # of listings)	log (total # of listed items)	log (total # of unique sellers)
	(1)	(2)	(3)
Panel A: Conditional on 116 categories that existed at the start of sample (June 2001)			
% protected (calculated by $\bar{p}_{k0}$)	-0.699**	-0.855**	-0.705**
	(0.184)	(0.222)	(0.155)
Observations	2,416	2,416	2,416
R-squared	0.887	0.821	0.907
Panel B: Full Sample			
% protected (calculated by $\bar{p}_{k0}$)	-0.602**	-0.812**	-0.617**
	(0.179)	(0.220)	(0.151)
Observations	2,797	2,797	2,797
R-squared	0.89	0.821	0.91

Note: Robust standard errors in parentheses, errors clustered by two-level product category, ** p<0.01, * p<0.05, + p<0.1. $\bar{p}_{k0}$ stands for the average transaction price of category k in the first month that k appeared in our analysis sample. All regressions control for product category fixed effects, year-month fixed effects, Aftwarning*$\bar{p}_{k0}$, and t*$\bar{p}_{k0}$, where t is defined as number of calendar months since June 2001.

Table 7: Results with Seller Fixed Effects (Linear Probability Model)

Dependent Variable	Seller Positive Feedback			Completed		log (final price)	
% predicted price protected by Eachnet	-0.040**		-0.039**	-0.010**	-0.011**	0.546**	0.548**
	(0.004)		(0.004)	(0.003)	(0.003)	(0.022)	(0.022)
% of protection | predicted p<=500		-0.038**					
		(0.004)					
% of protection | predicted p>500		-0.058**					
		(0.005)					
Predicted price (in thousand)	-0.022**	-0.018**	-0.017**	-0.011	-0.019		
	(0.004)	(0.004)	(0.004)	(0.085)	(0.085)		
log (seller score at time of listing)	-0.047**	-0.047**	-0.015**	0.001+	0.004	0.093**	-0.023
	(0.001)	(0.001)	(0.005)	(0.001)	(0.004)	(0.005)	(0.015)
=1 if seller score is missing or <=0	0.024**	0.024**	0.009	-0.164**	-0.113**	0.114**	-0.132**
	(0.004)	(0.004)	(0.014)	(0.003)	(0.009)	(0.014)	(0.046)
after protection * log(seller score)			-0.009+		0.007+		0.047**
			(0.005)		(0.004)		(0.015)
after protection * seller score missing or <=0			-0.004		-0.011		0.184**
			(0.017)		(0.011)		(0.053)
after warning * log(seller score)			-0.024**		-0.011**		0.073**
			(0.002)		(0.002)		(0.007)
after warning * seller score missing or <=0			0.033**		-0.049**		0.060+
			(0.011)		(0.007)		(0.032)
Observations	783,566	783,566	783,566	985,265	985,265	783,566	783,566
R-squared	0.269	0.269	0.27	0.548	0.548	0.657	0.657

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

Table 8: The Effect of Buyer Protection on Market Composition

	Fraction of new sellers (4)	Fraction of sellers old in Eachnet but new to this category (6)	log (average seller score) (10)	Fraction of seller score being missing (12)	Fraction of seller score being negative, missing or zero (11)	Fraction of transactions with positive seller feedback (7)	Fraction of transactions with negative seller feedback (8)	Fraction of transactions with seller warning (9)
%protected (calculated by $\bar{p}_{k0}$)	0.006	0.041*	0.394**	-0.073**	-0.091**	0.012	-0.010**	0.004
	(0.018)	(0.016)	(0.133)	(0.023)	(0.023)	(0.017)	(0.002)	(0.004)
Observations	2,416	2,416	2,343	2,416	2,416	2,416	2,416	1,594
R-squared	0.462	0.295	0.806	0.588	0.617	0.510	0.208	0.174
%protected (calculated by $\bar{p}_{k0}$)	0.001	0.038*	0.361**	-0.067**	-0.084**	0.021	-0.013**	0.002
	(0.017)	(0.016)	(0.126)	(0.022)	(0.022)	(0.017)	(0.005)	(0.004)
Observations	2,797	2,797	2,716	2,797	2,797	2,797	2,797	1,940
R-squared	0.462	0.326	0.799	0.577	0.604	0.502	0.183	0.167

Note: Robust standard errors in parentheses, errors clustered by two-level product category, ** p<0.01, * p<0.05, + p<0.1. $\bar{p}_{k0}$ stands for the average transaction price of category k in the first month that k appeared in our analysis sample. All regressions control for product category fixed effects, year-month fixed effects, Aftwarning*$\bar{p}_{k0}$, and t*$\bar{p}_{k0}$, where t is defined as number of calendar months since June 2001.

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

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

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

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

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