The Effect of Information Disclosure on Product Demand: Evidence from Yahoo! Auctions Taiwan

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We study the effect of information disclosure in resolving adverse selection by estimating the demand for a specific type of T-shirt sold on the Yahoo! Auctions platform. To reduce information asymmetry in Internet transactions, a seller usually voluntarily discloses product information by providing photos on the website. The disclosed information in the market we studied can be naturally separated into high and low quality levels. Not only does providing high-quality information which accurately reflects product characteristics increase consumer demand, but also an increase in the quantity of high-quality information will have a positive marginal effect. On the contrary, increasing the amount of low-quality information has almost no effect on demand.

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1 Introduction

Akerlof (1970)'s seminal paper points out that asymmetric information can create adverse selection, and consequently many potential gains from trades

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would not realize. In the past decade, Internet transactions have grown dramatically. Internet transactions often face severe information asymmetry because trade partners usually do not know each other and buyers do not see the product until it is delivered. The popularity of Internet transactions seems contradictory to the prediction of the adverse selection problem. Theories suggest that voluntary disclosure could be used to resolve the adverse selection problem (Cheong and Kim, 2004; Grossman, 1981; Jovanovic, 1983; Milgrom, 1981). In this paper, we demonstrate that the effectiveness of voluntary disclosure depends crucially on both the quantity and the quality of the disclosed information.

There are primarily two kinds of information asymmetry on Internet transactions. One is the uncertainty about the trade partner. For example, a buyer does not know whether the seller will honestly deliver the promised good after he/she makes the payment. Besides, a seller does not know if the buyer will honestly report the condition of the good after receiving it. The second kind of information asymmetry is about the exact product characteristics. Because the buyer cannot examine the product in person before making the payment, the actual characteristics might be different from the expected. While there have been many previous researches on the first kind of information asymmetry, there are fewer works on the second kind. In this paper, we focus on the information asymmetry about product characteristics.

One important reason behind the success of eBay, Yahoo!, and other Internet auction platforms is their reputation system. The system can reduce the problem associated with the uncertainty about the trade partner. It typically works in the following way. After each completed transaction, the buyer can give the seller an evaluation. The evaluation can be either positive, neutral, or negative. At the same time, the seller can evaluate the buyer in the same way. The auction platform records all the past evaluations for each user. As a result, a user is associated with a rating score, which equals to the number of positive evaluations minus the number of negative ones in the past. The rating score is usually displayed together with a user's ID on the webpage. Therefore, all other users can see the score readily. This score functions as a reputation system. A user with a high score must have received many positive evaluations in the past. Houser and Wooders (2006) find that a user can sell a product for a higher price if he/she has a higher rating score, but a buyer's score does not affect the transaction price. Moreover, Livingston (2005) shows that the marginal effect of a seller's rating score is

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positive but decreases rapidly when a seller cumulates a higher score. These findings mean that rating scores can reduce the problem associated with the information asymmetry on a seller's personality. Buyers have stronger demand when facing a seller with a higher rating score. On the other hand, a seller can block buyers who have a low score from bidding or purchasing the product. Therefore, uncertainty about a buyer's honesty can also be resolved by using the reputation system.

As for the information asymmetry arising from uncertainty about product characteristics, a seller can voluntarily disclose product information to reduce the uncertainty. Common methods of information disclosure include photos, texts, videos, and scanned images. Several previous researches find a positive relationship between consumer demand and the amount of disclosed information. Dewally and Ederington (2006) find that failure to provide a scanned image reduces the price by 12–17% in the eBay comic book market. Similarly, Melnik and Alm (2005) find a positive effect of scanned image on the price of noncertified coins sold on eBay. Nonetheless, they find the effect to be insignificant for certified coins. Jin and Kato (2006) use a field experiment to examine the sales of baseball cards on eBay. They find that buyers pay a higher price for baseball cards which are claimed to have better quality even though sellers often make untruthful claims on the quality. Using auction data from the sales of used cars in eBay Motors, Lewis (2011) shows that buyers are willing to bid a higher price when a seller provides more photos or more texts because seller of a high-quality car is willing to disclose more information than seller of a lower-quality car.[1]

Previous studies find that proving information in Internet sales has a positive effect on demand and the effect is positively correlated with information quantity. In this study, we contribute to the existing literature by accounting for information quality. It is usually difficult to measure the quality of information. Nonetheless, in the unbranded clothing market we studied, the photos provided by a seller can be naturally categorized into two quality types. The products in this market are usually made by imitating the design of famous brands. Although some sellers provide photos taken for the actual product, others only provide photos of the clothes being imitated. We regard the former type as high-quality information while the latter as

[1]Andrews and Benzing (2007) find a negative correlation between the price of a used car in eBay Motors and the number of disclosed pictures. However, their estimated coefficient might be biased because they do not consider endogeneity problem in the estimation.

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low-quality.[2] Note that our study is different from Melnik and Alm (2005)'s study of coins sales on eBay. In their study, coins are heterogeneous in certification. The effect of disclosed information differs, depending on whether the coin is certified, but the information itself is homogeneous across coins. On the contrary, our focus is the difference in the effect arising from the heterogeneity of information quality.

We investigate the causal effect of the amount of disclosed information on consumer demand. As Lewis (2011)'s theoretical model suggest, the amount of disclosed information is a seller's endogenous decision, depending on the unobserved product characteristics. Moreover, standard economic theory also suggests that unobserved characteristics affect a seller's pricing decision. Therefore, price is also an endogenous variable. To consistently estimate the marginal effect of disclosed information, we use instruments to construct moment conditions and estimate by the Generalized Method of Moments (GMM). We find that only high-quality information affect consumer demand. Increasing the amount of high-quality photos induces significantly higher demand, but the effect of adding a low-quality photo is small both economically and statistically.

Our findings indicate that providing more authentic information on actual products can help a seller to market its products better. On the contrary, showing more detailed information about the concept design for a product does not have a significant impact on consumer behavior.

The rest of the paper is organized as the following. In the next section, we briefly introduce the unbranded clothing market on the Yahoo! Auctions platform and discuss the information problem arising in this market. In Section 3, we describe the details about data collection and explain the variables used in our estimation. In Section 4, we outline the estimation method and discuss the instruments for identifying the causal relationship in our demand model, followed by showing our estimation results. Concluding remarks are given in the final section.

2 The Clothing Market in Yahoo! Auctions Taiwan

Our study uses data from Yahoo! Auctions Taiwan, which is one of the two largest Internet auction platforms in Taiwan. The Internet search giant Yahoo! started its auction service in 1998. Due to the competition from other

[2] In our sample, no seller provides both types of photos at the same time in a listing.

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Table 1: The most commonly used method of online shopping

Method	Percentage
Buying from online shopping sites	41
Using Buy-It-Now in auction sites	37
Bidding in auction sites	20
Using group buying sites	2

Source: Market Intelligence & Consulting Institute, Institute for Information Industry (2008)

Internet auction sites, Yahoo! ceased its auction service in most countries as of 2009. Only the Taiwan, Hong Kong, and Japan sites remain up and running.

Although Yahoo! still provides the auction service in Taiwan, many sellers use this platform as a channel to sell products at a fixed posted price. The rule in Yahoo! Auctions is similar to a standard ascending auction with a specified closing time. A seller can choose the starting bid of the auction. In addition, the platform allows a seller to set a 'Buy-It-Now' price by paying a small fee.[3] When an item is listed with a 'Buy-It-Now' price, anyone can buy it immediately at the posted 'Buy-It-Now' price regardless the bids having been submitted by others. Since no one would submit a bid higher than the 'Buy-It-Now' price, if a seller chooses the 'Buy It Now' price equal to the starting bid of the auction, the product can only be sold at the posted 'Buy-It-Now' price. For the clothing market in Yahoo! Auctions Taiwan, most products are sold by such a fixed posted price, despite the auction format. In fact, a recent survey shows using the 'Buy It Now' price in an auction site to purchase a good is much more common than bidding (See Table 1).

In this paper, we study unbranded new clothes sold by professional sellers. We exclude branded clothes because the reputation of a brand can also be an indicator for the quality of clothes. Besides, consumers can visit a brick-and-mortar store to learn the actual characteristics of branded clothes. For example, a consumer can try on the clothes in a brick-and-mortar store and then buy them from an Internet seller. On the contrary, consumers can know the product characteristics of unbranded clothes only through the

[3]The fee for setting a 'Buy-It-Now' price is one Taiwan dollar (TWD). The exchange rate in the sampling period for one US dollar is roughly 34.5 Taiwan dollars.

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information provided on the website by the seller. Therefore, the disclosed information should have a more direct impact on consumer demand.

Sellers in this market do not design the clothes by themselves. Instead, they imitate the design of famous brands or the design appeared in fashion magazines. Most sellers have few clothes in their stock. They adopt the 'make to order' strategy to fulfill their orders. As a result, sellers can supply as many items as consumers demand, and buyers usually need to wait for a few days after placing an order through the platform on Yahoo!

Because consumers cannot examine the products in person before making a payment, an important issue in this market is to convey the information about the actual products characteristics to consumers. Although some information can be easily described by texts, such as color, size, or fabric, many aspects of clothes are difficult to described by words, such as the graph on a T-shirt or the shape of sleeves. Consequently, for selling clothes on the Internet, sellers usually provide photos on the website.

However, the photos provided on the website differs in their quality levels. We can separate their quality levels naturally into high type and low type. Some sellers post the photos taken for the actual product, but others only post the images of the original clothes they imitate (for example, the photos appearing on the fashion magazines or the photos in the website of the original branded product). When photos of the actual product are posted, the information accurately reflects product characteristics, and we say the disclosed information is of high quality. On the other hand, if a seller only provides the images of the clothes being imitated, it is reasonable to expect the actual product to be somewhat different from the posted photos. We say the latter type of information is of low quality. Our empirical analysis is to test whether different sources of the photos affects the effectiveness of information disclosure on resolving the adverse selection problem.

3 Data

We collected all the sales listed under the category of *short-sleeve, round-neck T-shirts* on Yahoo! Auctions Taiwan ending during the period between March 10 and March 14, 2009. There are 164 observations in our sample. In order to include only professional sellers, we only collected sales listed as

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a 'featured item'.[4] In addition, to exclude branded products, we only include sales with a listed price less than 500 TWD (Taiwan dollars).[5]

Descriptive statistics of the data are presented in Table 2. All sellers set the starting bid equal to the 'Buy-It-Now' price in our sample. Consequently, all goods are essentially sold at a fixed posted price, determined by the seller before listing.

When listing a product, a seller needs to show the number of items available for sale. In this market, sellers typically list a very large number, such as 999, and then manufacture them after receiving orders.[6] Therefore, the number of available items is not a binding constraint for buyers. In a typical auction, buyers need to compete with each other to obtain the limited quantity of the items available for sale. This is not the case in the market we studied. A buyer can almost always obtain the product at the posted 'Buy-It-Now' price as long as he/she is willing to pay that price.[7] Given the posted price, the total transaction quantity reflects consumer demand for the product. This quantity is obtained by looking at the 'bidding history' on the webpage.

The dummy variable Quality indicates the quality of disclosed information. It equals one if the seller provides photos taken for the actual product. Its value is zero otherwise. To determine the quality of photos, we use two different definitions for this variable. Most of our empirical analysis is based on the first definition, but we also estimate the model under the second one as a robustness check.

1. The variable Quality = 0 only if the seller explicitly notes that the posted photos are not taken from the actual products, and Quality = 1 if the seller does not make such statements.
2. We ask two research assistants to subjectively make the judgements of

[4]Featured items are displayed with a colored background on the screen. It costs 40 TWD for each listing.

[5]Products with a price less than 500 TWD account for roughly 70% of listings in this category.

[6]The median number of the available items is 388, while the mean number is 453. The listing fee depends on the number of items available for sale. The fee is 3 TWD for each available item, but it is capped at 90 TWD. When there are more than 30 items available in one listing, the fee is fixed at 90 TWD.

[7]Because only two listings among the 164 observations in our sample sold out all available items, we decide to ignore the right censoring issue in our estimation.

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Table 2: Descriptive Statistics of Variables

Variable	Description	Mean	Std. Dev.	Min.	Max.
Dependent Variable					
Q	quantity of sales	21.87	36.47	1	303
Explanatory Variables					
Quality	(dummy) photos taken for actual products				
definition 1	explicitly noted by the seller	0.71	0.45	0	1
definition 2	subjectively judged by research assistants	0.67	0.47	0	1
Photo	number of photos	8.34	4.99	3	35
Price	price (Taiwan dollars)	197.44	57.83	75	450
Words	number of words in product description	14.41	20.76	0	96
Rating	seller's rating score	14,112	18,342	46	85,850
Negative	percentage of seller's negative rating	0.30	0.36	0	1.89
CVS	(dummy) sending to a convenient store possible	0.56	0.50	0	1
COD	(dummy) cash on delivery possible	0.66	0.47	0	1
FTF	(dummy) face-to-face transaction possible	0.12	0.32	0	1
Wait	maximal waiting time (days)	13.45	7.43	0	30
Material	(dummy) material described in the listing	0.93	0.26	0	1
Color	number of available colors	2.83	1.93	1	13
Phone	(dummy) describing seller's phone number	0.87	0.34	0	1
Duration	duration of the listing (days)	10.27	0.37	6.96	10.50
Instrumental Variables					
Order	(dummy) using an order system for checkout	0.91	0.28	0	1
Item	number of items listed by the seller on Yahoo! Auctions Taiwan at the same time	293.03	180.82	39	838
OtherPrice	average price of other items listed by the seller concurrently in the same category	197.17	49.19	99	333
OtherPhoto	average photo number of other items listed by the seller concurrently in the same category	8.37	3.43	3	21
NoOther	(dummy) whether the seller lists other item in the same category at the same time	0.18	0.39	0	1

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photo quality independently by checking the posted photos. When both assistants recognize the photos as a scanned image from a magazine or from other websites, we set Quality = 0. Otherwise, Quality = 1.

Because some sellers who provide scanned images do not explicitly state that the photos are not taken for the actual produce, there are more listings falling into the high-quality (Quality = 1) category under the first definition.

We measure the amount of information by counting the number of photos posted in each listing. Although the size of a photo may affect a consumer's perception of the product, we only consider the number of photos in our estimation. In addition to photos, we also count the number of words used in the 'product description' field and use a dummy variable indicating whether the material of the product is described in the listing to account for other aspects of information variation.

In the literature, a seller's reputation is known to be an important factor in determining a buyer's willingness to pay. We include two measures for the reputation: the seller's total rating score and the percentage of the seller's negative ratings in the past. Both are displayed together with the seller's ID on the product description webpage. Consequently, a buyer can easily uses these two variables to evaluate the seller's reputation, which in turn may affect a buyer's purchasing decision.

The shipping options may affect a buyer's demand. All sellers have the option of shipping by the postal service. There is no variation for this shipping method in the data. Nonetheless, there are variations on additional shipping options, including (a) allowing a buyer to pay at the time of delivery, (b) sending the product to a convenient store and collecting the payment at the store, (c) allowing a buyer to meet the seller in person and complete the transaction face to face. We use dummies COD, CVS, and FTF to indicate each of the three shipping options, respectively.

We will use several variables as exclusive instruments to construct moment conditions in the GMM estimation. The intuition for choosing these variables will be explained in the next section. First, Order is a dummy variable to indicate whether the seller uses an specific webpage for buyers to fill out address and other shipping information. Second, Item, is the number of all items listed by the seller at Yahoo! at the same time. This variable is a proxy for the scale of the seller. Third, OtherPrice is the average price of

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other items listed by the seller concurrently under the same category. Forth, OtherPhoto is the average amount of photos in other items listed by the seller concurrently under the same category. Finally, NoOther is a dummy variable indicating that the seller does not list any other item in the same category at the same time.

Based on the first definition of information quality, Table 3 shows the summary statistics for listings with high-quality and low-quality information separately. On average, listings with high-quality information sell more and have more photos posted on the website. They also tend to be more expensive and sold by sellers with a higher rating score.

4 Estimation

This section outlines our estimation approach and presents our estimation results.

4.1 Regression Model

Our main objective is to find the causal effect of adding a photo on demand. We consider a log-linear demand model with a constant demand elasticity. The regression equation is

$$\begin{aligned}\log Q = {} & \beta_0 + \beta_1 \log \text{Photo} + \beta_2 \log \text{Photo} \times \text{Quality} + \beta_3 \text{Quality} \\ & + \beta_4 \log \text{Price} + \beta_5 \text{Words} + \beta_6 \log \text{Rating} + \beta_7 \text{Negative} \\ & + \beta_8 \text{CVS} + \beta_9 \text{COD} + \beta_{10} \text{FTF} + \beta_{11} \text{Wait} + \varepsilon, \end{aligned} \tag{1}$$

where ε represents product characteristics unobserved to econometricians. These unobserved characteristics may include things such as the style of design, the graph on the T-shirt, or the size of the posted photos. We assume that ε is independent across sellers and has zero mean. The marginal effect of adding a photo is β_1 when low-quality information is provided (Quality = 0). The marginal effect is $\beta_1 + \beta_2$ when the seller provides high-quality information (Quality = 1).

To establish the causal relationship, we need to account for the potential endogeneity problem between Photo and the unobserved characteristic ε. As Lewis (2011)'s model shows, the amount of photos could be correlated with the unobserved characteristics ε. The seller of a product with better unobserved characteristics may want to incur more disclosure costs and provide

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Table 3: Descriptive Statistics by Information Quality

	Quality = 0		Quality = 1	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variable				
Q	6.70	5.97	27.97	41.52
Explanatory Variables				
Photo	6.91	4.89	8.91	4.94
Price	167.66	24.66	209.40	62.89
Words	2.04	6.20	19.38	22.45
Rating	1,842.68	898.30	19041	19,670
Negative	0.31	0.41	0.30	0.33
CVS	0.66	0.48	0.52	0.50
COD	0.60	0.50	0.69	0.46
FTF	0.04	0.20	0.15	0.35
Wait	9.23	5.06	15.21	7.56
Material	0.96	0.20	0.91	0.28
Color	1.68	0.66	3.29	2.08
Phone	0.89	0.66	0.85	0.35
Duration	10.17	0.18	10.31	0.42
Instrumental Variables				
Order	0.94	0.31	0.91	0.29
Item	215.04	88.37	324.36	198.47
OtherPrice	164.64	18.73	211.01	51.62
OtherPhoto	7.22	2.93	8.85	3.52
NoOther	0.15	0.36	0.20	0.40
observations	47		117	

more photos. As a result, both log Photo and the interactive term log Photo × Quality in the regression equation (1) might be endogenous. Besides, standard economics theory indicates that a firm's pricing decision is also affected by the unobserved characteristics ε. When the product has better unobserved characteristics, the seller would choose a higher price. Consequently, we allow ε to be correlated with log Photo and log Photo × Quality,

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and log Price. We assume ε is uncorrelated with other explanatory variables.

We estimate the regression equation (1) by the GMM. Although the equation can be also estimated by performing the two-stage least squares (2SLS), the unobserved characteristics ε is assumed to be homoskedastic across listings in the 2SLS. Instead, in our GMM estimation, the standard errors are robust to the presence of arbitrary heteroskedasticity.[8]

4.2 Exclusive Instruments

To deal with the endogeneity problem in our regression equation, we propose two sets of exclusive instruments. The first set consists of variables relating to the seller's firm size. The intuition for choosing these instruments is that the size of a firm may correlate with the cost of taking photos and producing a T-shirt due to economics of scales, but the size is unlikely to affect a consumer's demand directly (after controlling for a firm's reputation and other observed product characteristics). Hence, these instruments are correlated with the amount of photos and the price of the product. The dummy variable Order indicates whether the seller uses a online order system for the buyer to enter the mailing address and other shipping information. For a buyer, he/she always need to provide the information either through an online order system or through an e-mail to the seller. Therefore, we think this variable does not affect a buyer's decision. On the other hand, because of economics of scale, a seller with more items to sell is more likely to use an online order system and is also more likely to provide more photos on the webpage. The second instrument Item is the number of items sold on Yahoo! by the seller at the same time. The variable directly shows the size of the seller. We think this variable affects the cost of posting photos through economics of scale but has no direct impact on demand. In addition, we consider an interaction term log Item $\times$ Quality. The identification assumption is that, regardless photo quality, the number of listed items is uncorrelated with the unobserved characteristics ε.

The second set of exclusive instruments includes variables relating to the seller's concurrent listings. We compute the average price of the seller's other listings under the same T-shirt category during our sample period and

[8] We use the user-written command in Stata 'ivreg2' to estimate the regression equation. We estimate the model under the option 'gmm' so that the parameters are estimated using the optimal weighting matrix in the GMM.

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denote it as OtherPrice. When a seller has a lower cost in producing a T-shirt, he/she would choose a lower price for all kinds of T-shirts. Hence, the prices should be positively corrected. On the other hand, we do not think a buyer's demand depends the price of other T-shirts sold by the same seller. Similarly, OtherPhoto is the average number of photos among the seller's other listings under the same T-shirt category. When a seller has a lower cost of taking photos for one T-shirt, he/she is likely to have a lower cost for another. Hence, we expected the number of photos to be also positively correlated for T-shirts sold by the same seller. Finally, since some sellers only list one product under the *short-sleeve, round-neck T-shirts* category in our sample period, we cannot compute the average price nor the average photo number for these sellers. For listings of these sellers, we set OtherPrice and OtherPhoto to be zero and introduce a dummy variable NoOther to correct the bias resulting from missing values of OtherPrice and OtherPhoto. We can interpret the coefficient of NoOther as the joint effect of OtherPrice and OtherPhoto if the seller had listed any other product in this category.

4.3 Moment Condition

The moment condition for our GMM estimation is

$$E\left[\varepsilon \mathbf{z}\right] = 0. \tag{2}$$

The vector $\mathbf{z}$ includes two parts. The first part is the six exclusive instruments: Order, log Item, log Item $\times$ Quality, log OtherPrice, log OtherPhoto, and NoOther, and the second part consists of all the exogenous explanatory variables in the demand model (1): Quality, Words, log Rating, Negative, CVS, COD, FTF, Wait, and a constant term.

4.4 Estimation Results

Before moving to discuss our regression results, we use the first stage estimation of the 2SLS to show the validity of our exclusive instruments. Table 4 presents the results for the regressors of our preferred specification. The variables in the upper panel are the exclusive instruments. Most of them have explanatory power for the three endogenous variables. The F statistic for these exclusive instruments is greater than 7 for each endogenous variable. Furthermore, the χ^2 statistic for the Anderson canonical correlations likelihood-ratio test is 34.51, which has a p-value less than 0.0001.

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Table 4: First Stage Estimation of 2SLS

	log Photo	log Photo × Quality	log Price
Order	0.496***	0.347**	0.229**
	(0.138)	(0.139)	(0.090)
log Item	0.507***	−0.192	0.087
	(0.147)	(0.128)	(0.091)
log Item × Quality	−0.702***	0.090	−0.054
	(0.156)	(0.149)	(0.095)
log OtherPrice	−0.147	−0.071	0.786***
	(0.144)	(0.146)	(0.087)
log OtherPhoto	0.541***	0.487***	−0.0128
	(0.111)	(0.117)	(0.0643)
NoOther	0.392	0.711	4.147***
	(0.790)	(0.795)	(0.488)
Quality	3.619***	1.195	0.348
	(0.792)	(0.774)	(0.491)
Words	0.00335	0.00323	−0.00113
	(0.00190)	(0.00195)	(0.00123)
log Rating	0.199***	0.165***	−0.0059
	(0.056)	(0.054)	(0.0271)
Negative	0.219*	0.180	0.0123
	(0.129)	(0.125)	(0.0401)
CVS	−0.143*	−0.110	−0.0626
	(0.074)	(0.074)	(0.0412)
COD	−0.0330	−0.0717	−0.0261
	(0.0761)	(0.0792)	(0.0466)
FTF	−0.068	−0.043	−0.0281
	(0.113)	(0.105)	(0.0695)
Wait	−0.00240	0.00172	0.00075
	(0.00690)	(0.00685)	(0.00418)
Constant	−3.062***	−1.079	0.525
	(0.949)	(0.892)	(0.557)
R-squared	0.571	0.916	0.533
F-statistic for excluded instruments	36.46	7.74	18.69
p-value	0.000	0.000	0.000

Notes: Robust standard errors are in parentheses. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

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Therefore, the instruments qualify the requirement of being relevant to the endogenous variables.

The model parameters $(\beta_1, \beta_2, \cdots)$ are estimated by GMM. Table 5 presents the estimation results. We use the first definition for information quality (Quality) in the estimation. Some robustness checks are presented in the next subsection. Column (A) only includes the covariates related to information disclosure. Column (B) adds the two variables representing the seller's reputation. We add characteristics about shipping and waiting in Column (C), which is our preferred specification because it fits the data much better.

We now discuss the estimation results for the regression model (1). The marginal effect of adding low-quality photos on demand can be seen from the coefficient of log Photo. Although the coefficient is significantly positive in the first two columns, it is insignificantly different from zero after controlling for observed product characteristics in Column (C). Our estimation shows a significant difference in the marginal effect between high- and low-quality photos in all three specifications. The marginal effect of adding high-quality photos is the sum of the coefficients on log Photo and log Photo $\times$ Quality. Table 6 lists the point estimate for the sum and its robust standard error for each specification. The marginal effect of adding high-quality photos is significantly positive under all specifications. Increasing the amount of photos by one percent raises the demand by approximately 1.920 percents under our preferred specification, Column (C).

We compare the effects on demand resulting from different information qualities in Figure 1. Since the number of photos ranges between 3 and 17 for 90% of observations in our sample, we compute the point estimate of the effect on the demand for any given number of photos in this range, for both low- and high-quality information. The graphs show that, as long as there are more than four photos, demand is higher when information has better quality. For instance, consider a listing with eight photos, which is the median in the sample. Other things being equal, the amount of sales in a listing with high-quality information is 3.06 times that of a listing with low-quality information. This empirical finding indicates that providing high-quality information can boost the demand because it reduces the adverse selection problem. Moreover, providing high-quality information can also signal that the seller really has a product ready for sale, reducing the possibility of Internet fraud. One surprising finding in Jin and Kato (2006) is that buyers are willing to pay a higher price for nonverifiable claims in

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Table 5: Estimated Coefficients

	(A)	(B)	(C)
log Photo	0.927***	0.659*	−0.055
	(0.254)	(0.361)	(0.382)
log Photo × Quality	1.427***	1.639**	1.975***
	(0.479)	(0.711)	(0.597)
Quality	−2.039**	−2.558**	−2.988***
	(0.905)	(1.268)	(1.051)
log Price	−1.522***	−1.103**	−1.415***
	(0.493)	(0.442)	(0.458)
Words	0.00340	0.00560	0.00342
	(0.00527)	(0.00531)	(0.00484)
log Rating		0.060	0.096
		(0.128)	(0.106)
Negative		−0.310	−0.255
		(0.294)	(0.274)
CVS			0.386**
			(0.179)
COD			0.459*
			(0.238)
FTF			0.175
			(0.240)
Wait			−0.0044
			(0.0174)
Constant	7.700***	5.679*	7.753***
	(2.555)	(2.903)	(2.719)
R-squared	0.252	0.271	0.399
Hansen J-statistic	2.127	2.907	1.470
p-value	0.546	0.406	0.689

Notes: Robust standard errors are in parentheses. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

the sales of baseball cards. Our finding is more consistent with the theoretic prediction that only high-quality information has a impact on demand.[9]

[9]Jin and Leslie (2003) also find consumer demand to be sensitive to disclosing the information of the hygiene quality in their empirical study of restaurants in Los Angeles County.

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Table 6: The Marginal Effect of High-Quality Photos

	(A)	(B)	(C)
log Photo + log Photo × Quality	2.354***	2.298***	1.920***
	(0.401)	(0.516)	(0.456)

Notes: Robust standard errors are in parentheses. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

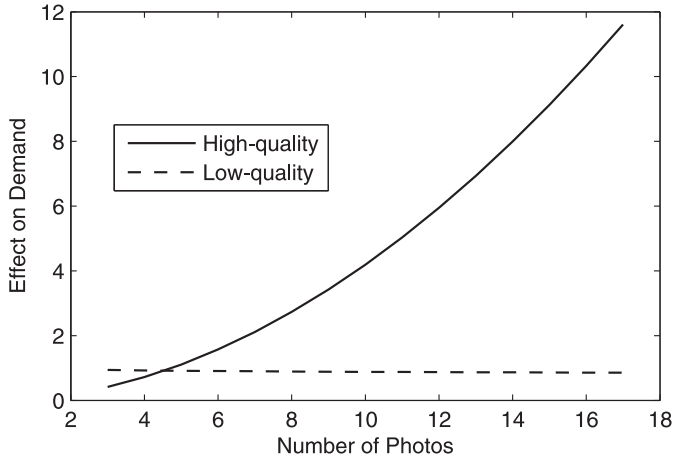


Figure 1: Effect of the Photo Numbers on Demand

Note: The vertical axis is the quantity of sales relative to the sales in a listing with one low-quality photo.

As for other explanatory variables, the demand curve has a negative slope, with demand elasticity near 1.415. There is almost no effect of providing longer text in product description, both statistically and economically. We think this is due to the difficulty of describing many product characteristics of clothes in text in a credible way. The accuracy of the text in the product description is difficult to verify even ex post. A picture is worth a thousand words for selling clothes.

In the previous literature, a seller's reputation is found to have a positive but rapidly declining impact on demand (Livingston, 2005). Our estima-

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tion indicates that one percent increase in the rating score raises the demand by 0.096 percents, but the effect is insignificant. Because the rating score is higher than 1,000 for over 90% of our observations, an insignificant effect of seller's reputation score is consistent with findings in previous researches. Besides, the percentage of negative ratings has no significant effect. This is probably because there is only small variation in this variable in our data. In fact, as Cabral and Hortaçsu (2010) find from eBay data, when a user cumulates too many negative ratings, he/she often abandons the ID and registers a new one. It is unlikely to observe a user ID associated with a large percentage of negative rating. Therefore, the percentage of negative ratings does not provide much information on a seller's past behavior.

Providing more shipping options has a positive effect on demand. Both the coefficient for picking up in a convenient store (CVS) and the coefficient for cash on delivery (COD) are significantly positive. Providing face-to-face transaction (FTF) also has a positive effect although it is insignificant. Besides, the waiting time has a negative effect on demand, but the effect is small and insignificant.

Finally, the Hansen overidentification test statistic is 1.470, which has a p-value 0.689. Therefore, we cannot reject the hypothesis that the instruments and ε are jointly uncorrelated at conventional significance levels. Our choice of the instruments appears to be reasonable.

4.5 Robustness Checks

We compare the preferred specification in the previous subsection with several alternatives specifications of regressors in Table 7 and alternative estimation approaches in Table 8. The first column in both tables replicates our preferred specification in Table 5.

In the second column of Table 7, we add quadratic terms of log Photo in the regression equation (1) to capture nonlinear effects of increasing photo numbers. Since quadratic terms are included in the regression, we include an additional exclusive instrument: $(\log \text{OtherPhoto})^2$. The standard errors for variables related to photo numbers all become very larger under this specification, indicating that we can only poorly identify these coefficients. Nonetheless, if we focus on point estimates and plot the estimated effects of photo numbers on demand in Figure 2, the graphs are qualitatively similar to those in Figure 1. Only adding the number of high-quality information

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Table 7: Coefficient Estimates with Alternative Specifications

	preferred specification	quadratic terms of log Photo	more observed characteristics	more interactive terms	OtherPrice as regressor	log Item as regressor
log Photo	−0.055	−1.728	−0.083	1.182	−0.054	−2.271
	(0.382)	(17.475)	(0.457)	(1.157)	(0.393)	(3.181)
log Photo × Quality	1.975***	3.169	2.064***	1.303	1.976***	4.703
	(0.597)	(20.347)	(0.743)	(1.224)	(0.610)	(4.397)
$(\text{log Photo})^2$		0.433				
		(4.934)				
$(\text{log Photo})^2 \times$ Quality		−0.354				
		(5.550)				
Quality	−2.988***	−3.863	−3.003**	−1.768	−2.989***	−7.412
	(1.051)	(16.945)	(1.182)	(2.101)	(1.061)	(7.432)
log Price	−1.415***	−1.865***	−1.549***	−2.393***	−1.414***	−1.938**
	(0.458)	(0.585)	(0.547)	(0.750)	(0.457)	(0.722)
Words	0.00342	0.00752	0.00589	0.00962*	0.00344	0.00214
	(0.00484)	(0.00521)	(0.00602)	(0.00524)	(0.00514)	(0.00905)
log Rating	0.096	0.159	0.093	0.328*	0.095	−0.102
	(0.106)	(0.124)	(0.114)	(0.225)	(0.132)	(0.335)
Negative	−0.255	−0.025	−0.280	−0.115	−0.255	−0.623
	(0.274)	(0.366)	(0.288)	(0.332)	(0.275)	(0.755)
CVS	0.386**	0.298	0.313	5.033***	0.386**	0.323
	(0.179)	(0.291)	(0.192)	(2.077)	(0.180)	(0.296)
COD	0.459*	0.346	0.482*	−0.600	0.459*	0.720
	(0.238)	(0.376)	(0.260)	(2.343)	(0.249)	(0.536)
FTF	0.175	−0.060	0.021	−2.240	0.175	−0.197
	(0.240)	(0.297)	(0.277)	(5.542)	(0.239)	(0.477)

(to be continued)

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(continued)

	preferred specification	quadratic terms of log Photo	more observed characteristics	more interactive terms	OtherPrice as regressor	log Item as regressor
Wait	−0.0044	−0.0192	−0.0097	−0.0335	−0.0043	−0.0300
	(0.0174)	(0.0306)	(0.0194)	(0.0328)	(0.0178)	(0.0382)
Material			−0.314			
			(0.361)			
Color			−0.0855			
			(0.0785)			
Phone			0.200			
			(0.351)			
log Photo × CVS				−2.544***		
				(1.128)		
log Photo × COD				0.531		
				(1.204)		
log Photo × FTF				1.195		
				(2.915)		
log OtherPrice					0.0005	
					(0.0507)	
log Item						0.412
						(0.439)
Constant	7.753***	8.107	8.858**	9.209**	7.751***	13.888*
	(2.719)	(15.821)	(3.479)	(4.480)	(2.717)	(8.229)
R-squared	0.399	0.428	0.397	0.239	0.398	0.049
Hansen J-stat.	1.470	1.220	1.494	1.405	1.472	0.063
p-value	0.689	0.543	0.684	0.704	0.479	0.802

Notes: Robust standard errors are in parentheses. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

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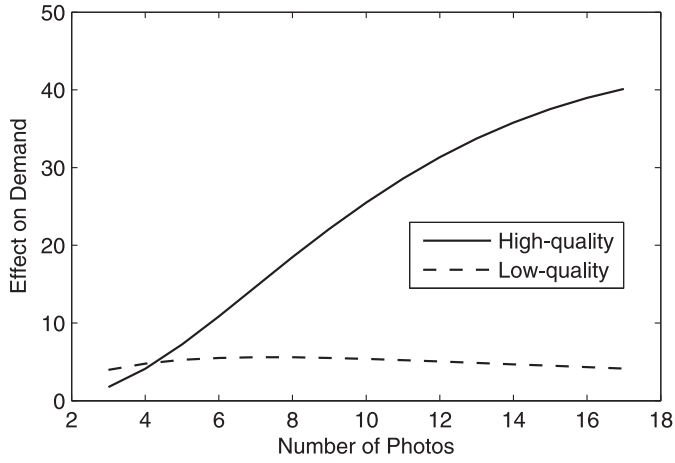


Figure 2: Effect of the Photo Numbers on Demand with Quadratic Terms

Note: The vertical axis is the quantity of sales relative to the sales in a listing with one low-quality photo.

impacts demand.[10]

In the third column of Table 7, we add some additional observed product characteristics, but there is almost no change in the estimation result. These additional characteristics have very little explanatory power.

Adding more interactive terms of log Photo with shipment options in column 4 does not change the result much.[11] The difference between adding high- and low-quality photos is still positive although it becomes insignificant. Besides, the sum of the coefficient on log Photo and log Photo × Quality is 2.110, which is significantly positive at 1% level. This means adding more high-quality information has a significantly positive effect, but adding more low-quality information does not. Moreover, the effect of increasing photo numbers is offset by providing the option of shipping to a convenience store. This is probably because a buyer can make the payment

[10]Figure 2 indicates that the marginal effect of adding more photos decreases in its number, suggesting that we might have overestimated the effect for large photo numbers when we restrict to a linear model in Figure 1.

[11]Three interactive terms are added as exclusive instruments in this specification: log OtherPhoto × CVS, log OtherPhoto × COD, and log OtherPhoto × FTF.

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when picking up the purchased product at the convenience store. As a result, there is less information asymmetry problem in a transaction, providing more information is less important.

When buying a T-shirt online, a buyer may want to purchase more than one item from the same buyer to save shipping cost. As a result, the characteristics of other items listed by the same seller concurrently might affect demand, and using log OtherPrice and log Item as instruments could be problematic. In the last two columns of Table 7, we include these two variables into the regression equation. Neither of them has a significant effect on demand.

Table 8 compares our GMM approach with three alternative estimation methods. Instead of using the GMM, we obtain the coefficient estimates by the 2SLS in the second column. The estimated coefficients are very close under these two estimation methods. We then ignore the endogeneity problem and estimate by the ordinary least squares (OLS) in the third column. Although most of the estimates are similar, the estimated coefficient for log Photo is larger under the OLS than under the GMM, but the estimate for the interactive term log Photo $\times$ Quality is smaller and insignificant under the OLS. This suggests that for sellers who post low-quality photos, the number of photos tend to be positively correlated with the unobserved product characteristics ε.[12] As a result, the OLS estimator is upward biased. On the contrary, for sellers posting high-quality photos, the number of photos tends to be negatively correlated with the unobserved characteristics ε.[13] The negative correlation is opposite to our conjecture, but it still indicates the importance of accounting for endogeneity in estimation.

In the final column of Table 8, we change the definition of information quality (Quality). Instead of using the description provided by the seller to distinguish high- and low-quality photos, we make the distinction by asking two research assistants to make subjective judgements. The estimated coefficients are qualitatively similar to those estimated under the first definition of Quality. Adding more low-quality photos still has no significant effect and the difference between adding high- and low-quality photos remains

[12]For listings with low-quality information, the estimation residuals have a weak positive correlation with the logarithm of the photos numbers. The correlation coefficient is 0.175.

[13]For listings with high-quality information, the correlation coefficient between the estimation residuals and the logarithm of the photos numbers is -0.379.

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Table 8: Coefficient Estimates with Alternative Approaches

	generalized method of moments	two-stage least squares	ordinary least squares	alternative definition of Quality
log Photo	−0.055	0.048	0.267	0.425
	(0.382)	(0.436)	(0.210)	(0.607)
log Photo × Quality	1.975***	1.626***	0.451	1.325**
	(0.597)	(0.673)	(0.342)	(0.674)
Quality	−2.988***	−2.305*	−0.340	−1.966*
	(1.051)	(1.206)	(0.624)	(1.142)
log Price	−1.415***	−1.615***	−1.417***	−1.487***
	(0.458)	(0.503)	(0.339)	(0.452)
Words	0.00342	0.00282	0.00624	0.00471
	(0.00484)	(0.00527)	(0.00573)	(0.00547)
log Rating	0.096	0.162	0.324***	0.145
	(0.106)	(0.122)	(0.097)	(0.094)
Negative	−0.255	−0.076	0.139	−0.140
	(0.274)	(0.314)	(0.255)	(0.249)
CVS	0.386**	0.267	0.257	0.314*
	(0.179)	(0.206)	(0.223)	(0.177)
COD	0.459*	0.458*	0.424*	0.336
	(0.238)	(0.258)	(0.250)	(0.248)
FTF	0.175	0.032	0.018	0.255
	(0.240)	(0.268)	(0.273)	(0.261)
Wait	−0.0044	−0.0167	−0.0121	0.0026
	(0.0174)	(0.0220)	(0.0228)	(0.0198)
Constant	7.753***	8.241***	5.556***	6.962**
	(2.719)	(2.872)	(1.903)	(2.954)
R-squared	0.399	0.445	0.511	0.439
Hansen J-statistic	1.470			1.344
p-value	0.689			0.719

Notes: Robust standard errors are in parentheses. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

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significant.[14]

5 Conclusion

We use data from an Internet marketplace, Yahoo! Auctions Taiwan, to show that disclosed information has a significant positive effect on demand only if the information has high quality. High-quality information can accurately reflect product characteristics. Our empirical study finds that demand responds only to the amount of high-quality information. When a seller provides photos taking for an actual product, one percentage increase in the number of photos can increase the number of sales by approximately 1.920 percentage points. On the other hand, when photos are taken for the product being imitated but not the actual product, the disclosed information is ineffective. Adding more low-quality information has almost no effect on demand. Our findings contribute to the existing literature by pointing out the importance of distinguishing the quality of disclosed information. Only high-quality information has a positive marginal effect in reducing the adverse selection problem.

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[14] In the reported estimation result, we define the quality to be high when either assistant classifies the information as high quality. We also try alternative definitions, including (a) defining quality as high only if both assistants classify it as high, and (b) defining quality solely on one assistant's judgements. The estimated coefficients are qualitatively similar across these definitions.

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訊息揭露對於產品需求的影響: 以台灣奇摩拍賣網站為例

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針對網路交易平台上的反淘汰問題, 本文透過對於需求函數的估計來衡量訊息揭露對於解決此一問題的效果。網路平台上的賣家, 通常可以利用張貼商品照片的方式來揭露商品的特徵, 藉以減少訊息不對稱所造成的問題。在我們所研究的奇摩網站 T 恤交易市場當中, 賣家所揭露的訊息可以依據照片內容區分爲高、低兩種品質。我們的實證結果發現, 張貼高品質訊息的照片不但會面對較高的商品需求, 而且照片的數量對於需求也有正的邊際效果。另一方面, 張貼低品質訊息的照片時, 照片張數對於商品的需求幾乎沒有任何影響。

關鍵詞: 資訊品質, 訊息不對稱, 估計需求, 訊息揭露
JEL 分類代號: C21, L15, L81

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