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

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Abstract

We empirically evaluate the effect of information disclosure on the demand for a specific type of T-shorts sold on the Yahoo! Auctions platform. Because buyers usually cannot examine the product directly when shopping online, information asymmetry may obstruct transactions. Sellers disclose product information by providing pictures on the website. Nonetheless, the disclosed information differ in both quantity and quality. High-quality information can reflect the product characteristics more accurately. Our estimation shows that the effect of providing more pictures on demand depends crucially on the quality of pictures. Demand significantly increases in the number of pictures only if the pictures provide accurate information on the product.

Keywords: Information quality, asymmetric information, demand estimation, information disclosure

JEL: C21, L15, L81

1 Introduction

Akerlof (1970)'s seminal paper points out that asymmetric information can create adverse

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selection, and consequently many potential gains from trades would not realize. In the past decades, Internet transactions have increased dramatically. Internet transactions often face strong 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. In this paper, we demonstrate that the information disclosed in an online marketplace can work to alleviate adverse selection. Consumer demand is higher when more information is disclosed. Nonetheless, the effectiveness of the disclosed information depends crucially on its quality. Only high-quality information has a significant impact on consumer demand.

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 pays the money. On the other hand, 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 exam 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 few 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 sites is their reputation system. The system 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 site 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. Therefore, all other users can see the score. 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 she has a higher rating score. On the other hand, buyer's score does not affect the transaction price. Moreover, Livingston (2005) show that the marginal effect of a seller's rating score is 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 lower score from bidding or purchasing the product. Therefore, information asymmetry about a buyer's personality can also be resolved by using the reputation system.

To study information asymmetry arising from uncertainty about product characteristics, Lewis (2009) proposes a model of adverse selection under costly information disclosure and verifies the theoretical predictions by using auction data from eBay Motors. Because providing information is costly, sellers with a better-quality product anticipate a higher surplus from transaction and tend to disclose more information (pictures, text, and graphs) on the web. On the other hand, buyers can infer the product quality by the quantity of disclosed information. As a result, buyers are willing to bid a higher price when a seller provides more information in the listing. This separating equilibrium helps reduce the adverse selection problem because buyers can use the quantity of information as a signal to infer the quality of a car.

While Lewis (2009)'s empirical study confirms the effect of information *quantity* on demand, we extend his work to account for information *quality*. It is usually difficult to measure the quality of information. Nonetheless, in the unbranded clothing market we studied, the pictures 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 pictures taken for the actual product, other sellers only provide pictures of the clothes being imitated. We regard the former type as high-quality information while the latter as low-quality.

Our empirical study investigates the causal effect of information quantity on consumer demand conditional on the quality of information. As Lewis (2009)'s model suggest, the quantity of information is likely to be a endogenous decision of the seller, depending on the unobserved product characteristics. Therefore, we use two stage least squares to estimate the demand. We find that one percent increase in the number of high-quality pictures can significantly increase the demand. On the contrary, the effect of adding a low-quality picture is small both economically and statistically.

The rest of the paper is organized as the following. In the next section, we briefly introduce the Internet unbranded clothing market used in our empirical study and point out the importance of information problem in this market. In Section 3, we present the details about data collection and explain the variables used in our estimation. In Section 4, we first discuss the instruments for identifying the causal relationship in our demand model, and then show our estimation results. Concluding remarks are in the final section.

2 The Clothing Market in Yahoo! Auctions Taiwan

We collected data from Yahoo! Auctions Taiwan, which is one of the two largest Internet auction sites in Taiwan. The Internet search giant Yahoo! started its auction service in 1998. Due to the competition from other 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 price. Specifically, when a seller chooses the "Buy It Now" price equal to the starting bid of an auction, the product can only be sold at this price.[1] For the clothing market in Yahoo! Auctions Taiwan, most products are sold by a fixed 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).

[1] The fee for setting a "Buy It Now" price is 1 Taiwan dollar (TWD). The exchange rate in the sampling period for one US dollar is roughly 34.5 Taiwan dollars.

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)

In this paper, we study unbranded new clothes sold by professional sellers. We rule out branded clothes because the reputation of a brand can also be an indicator for the quality of clothes. Besides, consumers can visit a brisk-and-mortar store to learn the quality of branded clothes or even to try on clothes and then buy them from an Internet seller. On the other hand, consumers can know the quality of unbranded clothes only through the information provided by the seller in the website. Therefore, the information should have 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 usually adopt the "make to order" strategy to fulfill their orders. As a result, buyers usually need to wait for a few days after placing an order through the platform on Yahoo!.

An important issue in this market is to convoy 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, seller always provide pictures on the listing. However, the qualify of pictures differs. Some sellers post the pictures taken for the actual product, while others only post the images of the original clothes they imitate (for example, the pictures appearing on the fashion magazines or the pictures in the website of the original branded product). Our empirical analysis is to test whether different sources of the pictures affect the effectiveness of convoying information. We say information is of high quality if the pictures are taken for the actual products. Otherwise, the information is of low quality.

3 Data

We collected all the sales listed in 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 163 observations in our sample. In order to include only professional sellers, we only collected sales listed as a "featured item".[2] In addition, to rule out branded products, we only consider the sales with a listed price less than 500 TWD (Taiwan dollars).[3]

Descriptive statistics are presented in Table 2. All the sellers set the starting bid equal to the Buy-It-Now price. Consequently, all goods are essentially sold at a fixed price, determined by the seller before listing. The description of a product is collected from its web page.

When listing a product, a seller needs to show the number of items available for sale. In this category, sellers typically list a very large number, such as 999, and then manufacture them after receiving orders.[4] Therefore, the number of available items is not a binding constraint for buyers. Different from a typical auction, buyers do not need to compete with each other to obtain the limited quantity of the items for available sale. The total transaction quantities reflect consumers' demand for the product. We can observe the quantity by looking at the bidding history.

The dummy variable $SOURCE$ indicates the quality of disclosed information. It equals one if the seller provides pictures taken for the actual product. Its value is zero if the seller uses other pictures. To determine the source of pictures, we use two different definition for this variable.

1. The variable $SOURCE = 0$ if the seller explicitly notes that the pictures are not taken

[2] Featured items are displayed with a colored background. It costs 40 TWD for each listing.

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

[4] The listing fee is 3 TWD per item, but it is capped at 90 TWD. When more than 30 items are available in one listing, the fee is fixed at 90 TWD.

Table 2: Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min.	Max.
SOURCE	pictures taken for actual products				
definition 1	explicitly noted by the seller	0.71	0.45	0	1
definition 2	subjectively judged by the authors	0.63	0.48	0	1
Q	quantity of sales	21.96	36.57	1	303
PHOTO	number of pictures	8.34	5.01	3	35
PRICE	price (Taiwan dollars)	197.55	58.00	75	450
WORDS	number of words in product description	14.05	20.31	0	96
RATING	seller's rating score	14195.15	18368.04	46	85850
NEGATIVE	percentage of seller's negative rating	0.30	0.35	0	1.89
CVS	sending to a convenient store possible	0.56	0.50	0	1
COD	availability of cash on delivery	0.66	0.47	0	1
WAIT	maximal waiting time (days)	13.45	7.43	0	30
DURATION	duration of the listing	10.28	0.39	6.96	11.46
FTF	availability of face to face transaction	0.12	0.32	0	1
MATERIAL	material described in the listing	0.93	0.26	0	1
COLOR	number of available colors	2.81	1.92	1	13
PHONE	describing seller's phone number	0.87	0.34	0	1
ORDER	using an order system for checkout	0.92	0.27	0	1
ITEM	number of items listed by the seller	294.49	180.40	39	838
MODEL	number of models hired by the seller	0.88	1.00	0	7

from the actual products, and $SOURCE = 0$ otherwise.

2. We subjectively make the judgement by checking the posted pictures. For instance, if pictures can be recognized as a scan from a magazine, we set $SOURCE = 0$.

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.

We measure the quantity of information by counting the number of pictures posted in the listing. Although the size of a picture may affect a consumer's perception of the product, we only consider the number of pictures in our estimation. In addition to pictures, we also count the number of words in product description and a dummy variable of material description to account for other aspects of information variation.

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

The shipping choices may affect a buyer's demand. All sellers have the option of shipping by the postal service or by a private shipping company. Some sellers allow a buyer to pay at the time of delivery (COD). Beside, there are additional shipping choices offered by part of the sellers: (1) Seller sends the product to a convenient store and buyer pays at the store. (2) Seller and buyer negotiate a place to meet and complete the transaction face to face. We use dummies CVS and FTF to indicate these two shipping options.

We will use three variables as instruments in the regression. The intuition for choosing these variables will be explained in the next section. The first instrument, $ORDER$, is a dummy variable to indicate whether the seller uses an specific webpage for buyers to fill out address and other shipping information. The second one, $ITEM$, 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

Table 3: Descriptive Statistics by Photo Quality

Variable	SOURCE=0	SOURCE=1
Q	6.70	28.15
PHOTO	6.91	8.92
PRICE	167.66	209.66
WORDS	2.04	18.91
RATING	1842.68	19200.03
NEGATIVE	0.31	0.29
CVS	0.66	0.53
COD	0.60	0.69
WAIT	9.23	15.16
DURATION	10.17	10.32
FTF	0.04	0.15
MATERIAL	0.96	0.91
COLOR	1.68	3.27
PHONE	0.89	0.85
ORDER	0.94	0.91
ITEM	215.04	326.68
MODEL	0.00	1.23

seller. The last instrument, $MODEL$, is the number of models hired by the seller.

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

4 Estimation

4.1 Model

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

$$\begin{aligned}\log Q = \beta_0 + \beta_1 \log PHOTO + \beta_2 \log PHOTO \times SOURCE + \beta_3 SOURCE \\ + \beta_4 \log PRICE + \beta_5 WORDS + \beta_6 \log RATING + \beta_7 NEGATIVE \\ + \beta_8 CVS + \beta_9 COD + \beta_{10} WAIT + \beta_{11} DURATION + \varepsilon \quad (1)\end{aligned}$$

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 pictures. We assume that ε is independent across listings, has zero mean, and is uncorrelated with all the explanatory variables except $\log PHOTO$ and $\log PHOTO \times SOURCE$.

The marginal effect is β_1 when a photo is not taking for the actual product ($SOURCE = 0$). The effect is $\beta_1 + \beta_2$ when the seller provides photos for the actual products ($SOURCE = 1$). To establish the causal relationship, we need to account for the potential endogeneity problem between $PHOTO$ and the unobserved characteristic ε. For instance, when an item has a better unobserved characteristic, a seller may post more pictures. Therefore, we allow ε to be correlated with $\log PHOTO$ and $\log PHOTO \times SOURCE$.

4.2 Exclusive Instruments

We propose three exclusive instruments to control the endogeneity of the number of pictures: $ORDER$, $ITEM$, and $MODEL$. The primary intuition for choosing these instruments is that the size of a firm may correlate with the cost of taking pictures 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 observed product characteristics). The first instrument $ORDER$ is a dummy variable indicating whether the seller uses a online order system for the buyer to enter the mailing address and other shipping information. For a buyer, 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 pictures on the webpage.

The second instrument $ITEM$ is the number of items sold 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 pictures through economics of scale but has no direct impact on demand.

The third instrument $MODEL$ is the number of models hired by the seller. When a seller hires more models, it is easier to find a model who fits the product best. As a result, we expect the seller to take more pictures to demonstrate the product. On the other hand, the number of models should have no direct effect on the product quality. Demand is unlikely to be affected.

In addition to the above three variables, we add two interaction terms $ORDER \times SOURCE$ and $ITEM \times SOURCE$ as exclusive instruments.[5] The identification assumption is that, conditional on the value of $SOURCE$, both $ORDEL$ and $ITEM$ are uncorrelated with ε. This assumption means that, regardless information quality, firm size is correlated with information quantity but uncorrelated with unobserved product characteristics.

4.3 Estimation Results

We estimate the regression equation (1) by the Generalized Method of Moments (GMM). Although the equation can be also estimated by performing two-stage least squares (2SLS), a standard assumption in 2SLS is to assume the unobserved characteristics ε to be homoscedastic across listings. Instead, in our GMM estimation, the standard errors are robust to the presence of arbitrary heteroskedasticity. [6]

[5] Because of collinearity, the interaction $MODEL \times SOURCE$ cannot be used as an instrument.

[6] 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

Table 4: Estimated Coefficients

	(A)	(B)	(C)
logPHOTO	0.935*	0.777*	-0.034
	(0.314)	(0.381)	(0.411)
logPHOTO×SOURCE	1.814*	0.940	1.305
	(0.626)	(0.837)	(0.828)
SOURCE	-2.700*	-1.290	-1.727
	(1.240)	(1.463)	(1.413)
logPRICE	-1.810***	-1.562***	-1.584***
	(0.359)	(0.317)	(0.313)
WORDS	0.00343	0.00642	0.00095
	(0.00751)	(0.00668)	(0.00647)
logRATING		0.195	0.249***
		(0.131)	(0.104)
NEGATIVE		-0.112	0.059
		(0.312)	(0.262)
CVS			0.309*
			(0.170)
COD			0.491**
			(0.202)
WAIT			-0.0253
			(0.0185)
Constant	9.157***	6.752***	7.592***
	(1.900)	(2.245)	(2.202)
Observations	163	163	163
R-squared	0.148	0.391	0.481
Hansen J-statistic	5.229	9.137	5.899
p-value	0.156	0.028	0.117

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

Table 4 presents coefficient estimates in the second stage of the 2SLS regression. We use the first definition for information quality ($SOURCE$) 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 some product characteristics in Column (C), which is our preferred specification.

Before moving to discuss our regression results, we show the validity of our exclusive

the GMM.

instruments. The first stage estimation of the 2SLS under the setup of Column (C) in Table 4. The first five variables are the exclusive instruments. Most of them have explanatory power for the two endogenous variables, $\log PHOTO$ and $\log PHOTO \times SOURCE$. The F values are greater than 10 in both columns. Furthermore, the χ^2 statistic for the Anderson-Rubin test is 16.99, which means the p-value is 0.0045. Therefore, the instruments qualify the requirement of being relevant to the endogenous variables.

We now discuss the estimation results for the regression model (1) shown in Table 4. The marginal effect of low-quality pictures on demand can be seen from the coefficient of $\log PHOTO$. Although the coefficient is positive in the first two columns at the significance level 10%, it is insignificantly different from zero after controlling for observed product characteristics. The effect of high-quality pictures is the sum of the coefficients of $\log PHOTO$ and $\log PHOTO \times SOURCE$. Table 6 lists the point estimate for the sum and its robust standard error for each model specification. The effect is significantly positive under all specifications. Increase the number of pictures by one percent can raise the demand by approximately 1.271 percents under our preferred specification, Column (C).

As for other explanatory variables, providing high-quality information by itself does not have significant impact on demand when comparing to providing low-quality information. The demand curve has a negative slope, with demand elasticity near 1.584. In this study, we assume price is uncorrelated with unobserved product characteristics ε. We do not deal with the potential endogeneity problem on price. If this assumption does not hold and price is positive correlated with ε (A seller may set a higher price for a product with a better unobserved quality ε.), our estimated coefficient on $\log P$ would bias upward, and the true demand elasticity would be higher than our estimate.

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. “A picture is worth a thousand words” for selling clothes.

As in the past literature, a seller’s reputation has important impact on demand. One percent increase in the rating score raises the demand significantly by 0.249 percents. Only

Table 5: First Stage Estimation of 2SLS

	logPHOTO	logPHOTO×SOURCE
ORDER	0.552*	0.022
	(0.313)	(0.115)
ORDER×SOURCE	0.045	0.550**
	(0.392)	(0.267)
logITEM	0.964***	0.252***
	(0.172)	(0.093)
logITEM×SOURCE	-1.091***	-0.330**
	(0.196)	(0.147)
MODEL	0.0863*	0.0826*
	(0.0441)	(0.0445)
SOURCE	5.569***	2.859***
	(1.036)	(0.717)
logP	-0.044	0.003
	(0.141)	(0.139)
WORDS	0.00185	0.00186
	(0.00221)	(0.00216)
logRATING	0.213***	0.185***
	(0.052)	(0.051)
NEGATIVE	0.351***	0.294**
	(0.146)	(0.132)
CVS	-0.121*	-0.0923
	(0.068)	(0.0621)
COD	-0.0098	-0.0689
	(0.0954)	(0.0893)
WAIT	-0.00057	0.00267
	(0.00678)	(0.00643)
Constant	-5.218***	-2.759
	(1.044)	(0.758)
Observations	163	163
R-squared	0.504	0.903
F-statistic	13.68	278.24

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

Table 6: The Marginal Effect of High-Quality Photos

	(A)	(B)	(C)
logPHOTO + logPHOTO×SOURCE	2.750***	1.717***	1.271**
	(0.546)	(0.650)	(0.592)

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

the other hand, the percentage of negative ratings has almost no effect on demand. This is probably because there is only small variation in this variable in our data. In fact, if a user cumulates too many negative ratings, he can give up the ID and register another ID. 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. Furthermore, an ID with a small rating score can either be a new user or an old user who registers a new ID to replace one with bad reputation. This also explain why the rating score is a good indicator for a user's reputation.

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

The p-value of the Hansen overidentification test is 0.117. Therefore, we cannot reject the hypothesis that the instruments and ε are jointly uncorrelated at the 10% significance level.

4.4 Robustness Check

We compare the preferred specification in the previous subsection with several alternatives. The estimates for the coefficients are shown in Table 7. The first column is our preferred specification, which is Column (C) in Table 4. We add some additional observed product characteristics in the second column, but there is almost no improvement in the model fit. These additional characteristics do not have much explanatory power. In the third column, we change the definition of $SOURCE$. Instead of using the description provided by the seller to distinguish high- and low-quality pictures, we make the distinction by our subjective judgement. The estimated coefficients are qualitatively similar to the preferred specification. In the last column, we ignore the endogeneity problem and estimate the model by ordinary least squares (OLS). Again, the results are similar. The estimate for β_1 is larger under OLS than under GMM, but the estimate for $\beta_1 + \beta_2$ is smaller under OLS. This suggests that for sellers who do post low-quality pictures, the number of pictures tend to be positively

Table 7: Coefficient Estimates with Alternative Specifications

	preferred specification	adding more characteristics	alternative definition of SOURCE	ordinary least squares
logPHOTO	-0.034	-0.030	-0.310	0.265
	(0.411)	(0.459)	(0.928)	(0.223)
logPHOTO×SOURCE	1.305	1.307	1.368	0.452
	(0.828)	(0.831)	(0.966)	(0.326)
SOURCE	-1.727	-1.738	-1.993	-0.338
	(1.413)	(1.326)	(1.697)	(0.588)
logPRICE	-1.584***	-1.502***	-1.428***	-1.418***
	(0.313)	(0.368)	(0.352)	(0.303)
WORDS	0.00095	0.00168	0.00072	0.00628
	(0.00647)	(0.00684)	(0.00583)	(0.00570)
logRATING	0.249*	0.246**	0.316***	0.323***
	(0.104)	(0.095)	(0.087)	(0.088)
NEGATIVE	0.059	-0.013	-0.068	0.140
	(0.262)	(0.256)	(0.306)	(0.229)
CVS	0.309	0.281	0.311	0.255
	(0.170)	(0.187)	(0.186)	(0.172)
COD	0.491**	0.448**	0.500**	0.426**
	(0.202)	(0.224)	(0.216)	(0.193)
WAIT	-0.0253	-0.0260	-0.0221	-0.0125
	(0.0185)	(0.0215)	(0.0181)	(0.0165)
FTF		-0.058		
		(0.280)		
MATERIAL		-0.170		
		(0.311)		
COLOR		0.0001		
		(0.0622)		
PHONE		-0.006		
		(0.330)		
Constant	7.592***	7.418***	6.831***	5.572***
	(2.202)	(2.607)	(1.799)	(1.714)
logPHOTO + logPHOTO×SOURCE	1.271**	1.277***	1.058**	0.717***
	(0.592)	(0.514)	(0.506)	(0.243)
Observations	163	163	163	163
R-squared	0.481	0.482	0.456	0.511
Hansen J-statistic	5.899	6.601	7.011	
p-value	0.117	0.086	0.072	

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

correlated with the unobserved product characteristics ε. As a result, the OLS estimator is upward biased. On the contrary, for sellers posting high-quality pictures, the number of pictures tends to be negatively correlated with the unobserved characteristics ε.

Since the data were collected from five consecutive days, we do not consider seasonality effects. As for the weekend effect suggested by Lucking-Reileyw, Bryanz, Prasad, and Daniel-Reeves (2007). In an unreported specification, we add a dummy variable to indicate whether a listing ends on weekend. We do not find any significant effect of this variable.

5 Conclusion

We use data from an online marketplace, Yahoo! Auction Taiwan, to show that the quantity of information has a positive effect on demand only if the quality of information is high. When a seller provides pictures taking for an actual product, one percentage increase in the number of pictures can increase the number of sales by approximately 1.376 percentage points. On the other hand, when pictures are taking for the product being imitated but not the actual product, adding more pictures has almost no effect on demand. Our findings are consistent with Lewis (2009)'s theoretical prediction that sellers selectively disclose costly information. Providing more high-quality information is essentially a signal for better product quality.

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