**Academic Journal of Economic Studies**
**Vol. 4, No. 4, December 2018, pp. 96–101**
**ISSN 2393-4913, ISSN On-line 2457-5836**

# Online Trading and Adverse Selection in Smartphone Market

**Fulgence Dominick Waryoba**

*School of International Education, Capital University of Economics and Business, No.2 Jintaili, Chaoyang District, Beijing*
*St. Augustine University of Tanzania, P. O. Box 307, Mwanza Tanzania, Email: fuldominick@yahoo.com*

***Abstract*** *Information asymmetry that dominates almost all market operations deters market performance and in some markets may lead into non-existence of market due to adverse selection problem. This paper hypothesizes that online trading reduces adverse selection problem in Smartphone market. The findings show that high quality Smart phones sell more than low quality Smart phones. Therefore, trading online induces signaling which reduces the problem of information asymmetry thereby offsetting adverse selection problem.*

***Key words*** Information asymmetry, adverse selection, signaling

**JEL Codes**: D82, D83



## 1. Introduction

In countries like Tanzania, it is common to hear people complaining about fake Smart phones. Two of my friends bought Smart phones from a Smartphone vender. Two days later, they discovered some phone malfunctioning, and each of these phones had no warrant. One of them decided to claim for money refund, and she was luck to be granted. But the other got scared of possible consequences and stayed with a lemon. There was no enough room for the two customers to gain product quality knowledge.

In any exchange of goods and services, individuals are interested in maximize their utility. Each one is making decision on exchange basing on the fact that the decision improves his or her welfare. In Yew's, (1974) terminology, the business will maximize his utility not his profit. Any plan chosen by the decision maker to consume today or later is because it maximizes utility (Stortz, 1956).

Information distribution across market participants can have a deep and sometimes shocking impact on market equilibrium. Definitely, asymmetric information deters market performance as mutually beneficial trades go unexploited. This failure of market outcomes to be Pareto efficient is the most troubling aspect from a normative perspective (Jehle and Reny, 2011). Asymmetric information can lead into adverse selection in used car market (Akerlof, 1970), and labor market (Spence, 1973), and moral hazard in employer-employee relationship (Grossman and Hart, 1983).

Any additional information whether perfect or imperfect, informative or uninformative, plays a significant role in improving the payoff among market participants. So it does not matter on the accuracy of information given, adding more information improves the welfare of participants (Holmstrom, 1979). In this study, it is hypothesized that online Smartphone trading enhances more signals, thereby improving market participants' welfare by reducing adverse selection problem.

## 2. Literature review

In the market for lemon, there are four types of cars traded in the market. The new cars and used cars, the bad and good cars. The new car can be good or bad and the used car can be good or bad as well. The buyer cannot tell the quality of the car he or she is buying. However, the buyer knows with probability q that the car is good and probability (1-q) that the car is bad. The probability q is the proportion of good cars produced and (1-q) is the proportion of bad cars produced. After owning a specific car, for a period of time, the owner learns the quality of the car and assigns a new probability that his car is a lemon. The current estimate by the owner is now more accurate than the previous estimate (Akerlof, 1970).

An information asymmetry has now developed because the sellers have more knowledge about their car than the buyers. Since it is impossible for the buyer to tell the quality, good cars and bad cars must continue to sell at the same price. It is obvious that used cars cannot have the same valuation as new cars-because owners of bad cars could sell their cars at the new car price and get a new car with probability q that it is of high quality. Therefore owners of good cars are locked in. They cannot get the value of their car neither can they get the expected value for the new car. In such circumstances, the bad cars drive out the good cars, and may lead into none existence of market (Akerlof, 1970).

When there are two types of sellers, new car and used car dealers, there is a possibility of reducing adverse selection. The assumption here is that the new car dealers sell used car too, while used car dealers sell only used cars. The difference is that the used cars from the new car dealer are of high quality than the used cars from the used car dealer. In this case the used car dealer offers an opportunity to the buyer of a substitute for the used cars. So when the new cars seem expensive to the buyer, there is always a substitute for new cars which is affordable and better than if it could have been purchased from the used car dealer (Genesove, 1993).

New car leasing has also been a response towards adverse selection problem in the secondary car market. A car that was leased when new is purchased at a higher price than a car that was purchased when new (Johnson and Waldman, 2010). Nevertheless, buyback pricing of leased cars has also been another effective mechanism to curb adverse selection. The fact that manufacturer pays low price to low quality cars and high price to the high quality cars, buyback provide an incentive for good car maintenance (Pierce, 2007).

The advancement in internet advertisements has advanced the solution toward adverse selection. High quality sellers, given price premium incentives, disclose more information than low quality sellers (Lewis, 2011). High quality online sellers provide high-cost easy-to-identify signals, which are unprofitable for low quality sellers to provide. Therefore, signaling reduces adverse selection problem (Mavlanova *et al.*, 2012). However, price premium incentives are necessary to encourage signaling by high quality sellers. On the other hand, legal sanctions are necessary to discourage low quality sellers from giving false quality information. Cheating benefits need to be outweighed by cheating costs for moral hazard problem to vanish (Mishra *et al.*, 1998).

## 3. Methodology of research

### 3.1. Data

This study conducted a survey on a sample of 221 Samsung Smart phones traded through eBay. Information on price, quantity sold, and Smartphone conditions have been collected to aid the analysis. The quantity sold stands for demand on buyer's side, and when multiplied with price it turns into revenue or sales on supplier's side. Price is given in Yuan while the quantities demanded are unit less, however measured in terms of Yuan in case of sales. The quantity demanded is added with unit to avoid applying logarithm on zeros. The Smartphone condition, or quality, has been categorized into seven dummy variables as follows:

*New:* All brand-new, unused, unopened, and undamaged items in their original packaging fall in this category.

*Used*: All phones previously used but look original according to information provided by the seller, fall in this group. *Manufacturer Refurbished (Manufacturer):* this group contains phones which have been professionally restored to working order by a manufacturer or manufacturer-approved vendor. This means the phone has been inspected, cleaned, and repaired to meet manufacturer specifications and is in excellent condition. This item may or may not be in the original packaging.

*Seller Refurbished (Seller):* All phones restored to working order by the eBay seller or a third party not approved by the manufacturer. This means the item has been inspected, cleaned, and repaired to full working order and is in excellent condition. This item may or may not be in original packaging.

*Used with Cracks (Usedcracks):* All phones with LCD heavy scratches, cracks on the screen or camera not functioning properly have been grouped into this category.

*New Other*: A new, unused item with absolutely no signs of wear. The item may be missing the original packaging, or in the original packaging but not sealed. The item may be a factory second or a new, unused item with defects.

*For parts or not working (nonuse):* An item that does not function as intended and is not fully operational. This includes items that are defective in ways that render them difficult to use, items that require service or repair, or items missing essential components.

Table 1 explores important information concerning data used in this study. Discussion concerning the nature of the data to some extent starts opening the doors of our expectations basing on the hypothesized effect of signaling as a solution to adverse selection.

*Table 1*. Variable Characteristics

| Smartphone | Quantity | Percentage | Average Price | Observations |
|---|---|---|---|---|
| New | 13,682 | 29.24 | 1,531.32 | 66 |
| Used | 7,287 | 15.57 | 1,436.82 | 55 |
| Manufacturer | 3'401 | 7.27 | 1,174.75 | 12 |
| Seller | 16,858 | 36.03 | 1,475.55 | 38 |
| Used Cracks | 2 | 0.004 | 1,258.76 | 21 |
| New Other | 5,556 | 11.87 | 1,850.23 | 22 |
| Non Use | 6 | 0.013 | 833.15 | 07 |
| Total | 46,792 | 100.0 | | 221 |

***Source:*** eBay collected raw data.

From Table 1, regardless of their models, a total number of 221 Samsung Smart phones have been surveyed on eBay trading. Out of 221 observations, about 29.24 percent is occupied by new Smart phones, 15.57 percent used, 7.27 percent manufacturer refurbished, 36.03 percent come from seller refurbished, 0.004 percent used phones with cracks, 11.87 percent new other, and about 0.013 percent from phones identified not for use. On average, *new other* seems to be the most expensive Smartphone in the sample however; it ranks the fourth in terms of percentage of the total demand. This highlights that here quality is not reflected in price level, that is, low quality but high price.

The price of *seller* refurbished Smartphone is slightly higher than that of *used* Smartphone category. But the demand is higher for the former than for the later. Intuitively, buyers have gained knowledge that *seller* refurbished Smart phones have higher qualities than used but unrepaired Smart phones. It is simple to tell that if they are in good condition they should not be returned to the seller. This made refurbished Smart phones more preferred than any other category in Table 1. Because even for *manufacturer* refurbished, only 12 members included in the sample but 3,401 units have been sold. Surprisingly, in the sample, refurbished category is more demanded than even *new* Smart phones. Refurbished are almost like new, have been tested to meet standards, and cheaper than new one. As a matter of facts, it is the most attractive category in the study sample. *Used cracks* comes the last, outweighed even by *nonuse* category because the price is too high even greater than that of *manufacturer* refurbished category. That is why, out of 21 members surveyed only 1 has managed to sell 2 at a price of 1,030.04 Yuan.

Information on Smartphone condition has been appropriately coded to get appropriate effect of quality on demand. The currency unit is Yuan, but does not mean the research is based on Chinese customers, because online trade goes beyond country boundaries. The study is concerned with testing the hypothesis that online trade reduces information asymmetry and therefore offsets adverse selection problem. Given time limitation, the study limits only on a sample of 221 Samsung Smart phones traded through eBay.

3.2. Model

Theoretically the consumer decision to purchase is a function of other factors like quality of the product, and price of the product. So the general variable relationship is given as

$$y_i = f(x_i) \tag{1}$$

However, equation (1) does not give us any form of the relationship between dependent and independent variables whether linear or nonlinear. The variables in this study are of different nature, some are in level form and others are in logarithmic form. This relationship is presented in the econometric model as:

$$Y_i = P_i^{\alpha_1} \exp\left( \alpha_0 + \sum_{j=2}^{k} \alpha_j X_{ji} + u_i \right) \tag{2}$$

Where $Y_i$ is the demand for the *i-th* phone, $P_i$ is the price for the *i-th* phone, and $X_{ij}$ stands for the dummy variables previously explained. There are seven dummy variables, but *new* is taken as the base variable which makes the model to have six dummy variables, so, *k*=7. $\alpha_j$ stands for the coefficient of the *j-th* dummy in the model. It is the difference in demand between new smartphone and *j-th* smartphone. $\alpha_1$ is the price elasticity of demand and $\alpha_o$ is the constant coefficient for new category. Finally, $u_i$ is the error term assumed to be identically and independently distributed. Equation (2) above must be linearized in order to be estimated. As a matter of facts, the logarith is introduced to get the following equation in an empirical expression.

$$\log(demand_i) = \alpha_0 + \alpha_1 \log(price_i) + \alpha_2 used + \alpha_3 manufacturer + \alpha_4 seller$$
$$+\alpha_5 usecracks + \alpha_6 newother + \alpha_7 nonuse + u_i \quad (3)$$

Where; $demand_i$ is the demand for the $i^{th}$ phone, $price_i$ is the $price_i$ for the $i^{th}$ phone, used = 1 if the phone is used with no scratches, 0 otherwise, manufacturer = 1 if the phone is manufacturer refurbished, 0 otherwise, seller = 1 if the phone is seller refurbished, and 0 otherwise, usecracks = 1 if the phone is used with cracks or fractures, 0 otherwise, newother = 1 if the phone is falls under new other, 0 otherwise, and nonuse =1 if the phone is for parts or not working, and 0 otherwise. Here, new is used as a base variable and so omitted to avoid the problem of dummy variable trap.

3.3. Estimation Techniques

*Coefficient Diagnostic Tests*

The ordinary least squares (OLS) estimation shows that four variables, namely price, manufacturer, seller, and newother, are statistically insignificant at 5 percent. A Wald test led into removal of seller from the model. However, the removal of seller, made manufacturer insignificant, and as a matter of facts, seller and manufacturer are merged to form a new variable namely refurbish, because they are all refurbished. OLS on the new model resulted into three variables, namely price, refurbish, and new other, being statistically insignificant. However, this time a Wald test proved they are statistically different from zero.

The F-Statistics from Table 2 are far greater than their corresponding critical values, necessitating the rejection of null hypothesis that the variables are jointly statistically insignificant. For specific variable, only seller should be dropped from Model 1, but in Model 2, each variable passes the test. A test for stability to check whether there is functional form misspecification in Model 2 is done to avoid any biasness from omission of important variables.

*Table 2*. Wald Test Results

| Model 1 | | Model 2 | |
|---|---|---|---|
| **Variable** | **Coefficient** | **Variable** | **Coefficient** |
| Price | 3.81**(1.791) | Price | 3.99**(1.760) |
| Manufacturer | -1.67***(0.372) | Refurbish | -1.68***(0.372) |
| Seller | 0.71(0.626) | Newother | -3.21***(0.260) |
| Newother | -3.21***(0.260) | | |
| F-Statistic (4, 213) | 55.47 | F-Statistic (3, 214) | 59.37 |

***Note***: ***, **, and * stands for significant levels at 1, 5, and 10 percent. Standard errors are given in parentheses.

*Stability Test*

In stability test, using Ramsey RESET Test with powers of fitted values from 2 to 3, we get F- Statistic (2, 212) of 0.135 which is far less than the critical value of 3.00 at 5 percent level. We fail to reject the null hypothesis of no functional form mispecification in the regression. Therefore, it is true that Model 2 is functionally well specified.

*Heteroskedasticity Test*

A well specified model means that the coefficients are not biased. However, a test for heteroskedasticity is important as its presence invalidates the standard errors used in making statistical inferences (Wooldridge, 2013). For the purpose of conserving the degrees of freedom, Model 2 is estimated using OLS to get residual and residual square. Then fitted values and their square are obtained. Equation (4) is estimated using OLS to test the null hypothesis $H_o$:$\delta_1$ = 0, and δ = 0.

$$\hat{u}_i^2 = \delta_0 + \delta_1 \widehat{demand}_i + \delta_2 \widehat{demand}_i^2 + error \quad (4)$$

From Table 3, δ ≠ 0, and is statistically significant at 5 percent levels of significance, and $\delta_2$ ≠ 0 and is statistically significant at 10 percent levels of significance. Even the F-Statistics of 6.34 is greater than the critical value of 3.00 which makes us reject the null hypothesis of no heteroskedasticity. Therefore, Model 2 should be estimated using weighted least squares (WLS) approach. The estimation results for predicted demand are given in Table 4. The WLS improves the explanatory power of the model. It explains about 91 percent of the variation in the predicted demand. Two variables, namely *price* and *newother* are statistically insignificant, but especially *price* under a one tail t-distribution. They are not excluded from Model 2 to maintain homoskedasticity after WLS estimation. *Price* has the expected sign, but its impact on the predicted demand for Smartphone is economically very low and statistically very insignificant. Therefore we cannot talk about the effect of price in the WLS model.

Holding other factors constant, the predicted demand for *used* Smart phones is about 138 percent less than the predicted demand for *new* Smart phones and the difference is economically large and statistically significant at 5 percent levels of significance. Information signals help customers identify the quality of Smartphone and therefore if price is the same, customers buy high quality phones. Other factors being equal, the predicted demand for refurbished Smart phones is 104 percent higher than the predicted demand for *new* Smart phones. This is not surprising because refurbished phones have been tested and customers believe they are more durable perhaps than the *new* Smart phones. The fact that refurbished Smart phones are slightly cheaper than new Smart phones, makes customers rather more satisfied with refurbished than new Smart phones. This confirms our a prior predicted effect in Table 1, where lower average price of refurbished phones results into higher quantity demanded for refurbished Smart phones than for *new* Smart phones.

*Table 3*. White Heteroskedasticity Test

| Variable | OLS | Standard Error |
|---|---|---|
| $constant$ | -0.04 | 1.285 |
| $\log(\widehat{demand})$ | 3.49*** | 1.528 |
| $[log(\widehat{demand})]^2$ | -0.60* | 0.382 |
| R-squared | 0.06 | |
| F-Statistics | 6.34 | |
| Observations | 221 | |

***Note:*******, * indicates significant at 1, and 10 percent respectively.

*Table 4*. Estimation Results for Model 1 and 2

| | Model 1 | Model 2 | |
|---|---|---|---|
| Variable | OLS | OLS | WLS |
| *Constant* | 3.81** (1.791) | 3.99** (1.760) | 3.998*** (0.9648) |
| *Price* | -0.08 (0.248) | -0.11 (0.244) | -0.06 (0.131) |
| *Used* | -1.67*** (0.372) | -1.68*** (0.372) | -1.38*** (0.230) |
| *Refurbished* | | 0.29 (0.425) | 1.04*** (0.244) |
| *Usedcracks* | -3.20*** (0.260) | -3.21*** (0.260) | -3.54*** (0.129) |
| *Newother* | -0.38 (0.558) | -0.38 (0.556) | -0.43* (0.279) |
| *Nonuse* | -3.00*** (0.390) | -3.01*** (0.390) | -1.63*** (0.119) |
| *Manufacturer* | 0.71 (0.626) | | |
| *Seller* | 0.16 (0.487) | | |
| R-Squared | 0.25 | 0.25 | 0.91 |
| Adjusted R-Squared | 0.23 | 0.23 | 0.90 |
| F-Statistics | 10.18 | 11.78 | 151.30 |
| Observations | 221 | 221 | |
| Observations after Adjustment | | | 96 |

**Note**: ***, **, and * indicates significance at 1, 5, and 10 percent levels. Standard errors are given in parentheses.

Ceteris paribus, the predicted demand for nonuse Smart phones is about 163 percent less than new Smart phones. The nonuse Smart phones are only purchased for special repair purposes. As a matter of facts, they cannot sell more than new Smart phones. For the case of *newother* Smart phones, other factors being equal, the predicted demand for *newother* Smart phones is about 43 percent less than that of *new* Smartphone and the difference is statistically significant at 10 percent levels of significance under one tail t-distribution. This still confirms the highlighted comparison in the data section. Obviously, newother are unopened Smart phones but sometimes with defects, therefore, this group is expected to sell less than *new* Smart phone category.

## 5. Conclusions

From the findings it is clear that releasing more information helps to curb adverse selection problem arising from asymmetric information. Therefore, online trade enhances more signals to customers. The buyer is exposed to many sellers and has enough room to gain knowledge about the quality. Purchasing decision is done based on the quality information which all market participants have, and if the quality is not up to expectations, eBay provides a return warranty. Therefore trading online for the case of Smart phones improves the welfare of both buyers and sellers. Buyers buy expensive products because the quality is reflected in the price. So the hypothesis that online trading reduces information asymmetry thereby offsetting adverse selection holds water in the Smartphone market at least for the sample utilized in this particular study. The study managed to illustrate that quality and price are the main determinants of demand for Smart phones, specifically Samsung. However, one brand is not enough to give a complete picture given the fact that there are more than ten Smartphone brands which are traded online. For this particular study, it was almost impossible to capture all brands due to time constraint. So, future studies will be more informative and comprehensive if they include other brands like Apple, Lenovo and others which are operating in the Smartphone world.

## Acknowledgement

This is a revised Microeconomics term paper which was submitted to the School of Economics at Capital University of Economics and Business. Thanks to the availability of trade information from eBay. The views of this paper remain solely those of the author.

## References

Akerlof, G A. (1970). "The Market for "Lemons": Quality Uncertainity and the Market Mechanism." *The Quarterly Journal of Economics*: 488-500.
Genesove, D. (1993). "Adverse Selection in the Wholesale Used Car Market." *Journal of Political Economy*, 644-665.
Grossman, S. J, and Hart, O.D. (1983). "An Analysis of the Principal-Agent Problem." *Econometrica*, 7-45.
Holmstrom, B. (1979). "Moral Hazard and Observability." *The Bell Journal of Economics*, 74-91.
Jehle, G. A, and Reny, P.J. (2011). *Advanced Microeconomic Theory.* Beijing: China Renmin University.
Johnson, J. P, and Waldman, M. (2010). "Leasing, Lemons, and Moral Hazard." *The Journal of Law and Economics*, 307-328.
Lewis, G. (2011). "Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors." *The American Economic Review*, 1535-1546.
Mavlanova, T., Bebunan-Fich, R. and Koufaris, M. (2012). "Signaling Theory and Information Asymmetry in Online Commerce." *Elsevier-Information and Management*, 240-247.
Mishra, D. P., Heide, J.B. and Cort, S.G. (1998). "Information Asymmetry and Levels of Agency Relationships." *Journal of Marketing Research*, 277-295.
Pierce, J. L. (2007). *Manufacturer Lease Pricing and Adverse Selection.* St. Louis: Washington University.
Spence, M. (1973). "Job Market Signaling." *The Quarterly Journal of Economics*, 355-374.
Stortz, R. H. (1956). "Myopia and Inconsistency in Dynamic Utility Maximization." *The Review of Economic Studies*, 165-180.
Wooldridge, J. M. (2013). *Introductory Econometrics: A Modern Approach.* Asia: Cingage Learning.
Yew, K. N. G. (1974). "Utility and Profit Maximization by an Owner-Manager: Towards a General Analysis." *Journal of Industrial Analysis*, 97-108.