The effect of dishonest sellers on e-commerce: an agent-based modeling approach

*Yi-Chen Huang*

*Tak-Yu Cheng*

*Bin-Tzong Chie*

Abstract

This paper studies dishonest sellers in the e-commerce market, specifically their impact on the market under different conditions. We consider the role of consumers’ social and individual learning and social network branches on the market. We rely on a quality uncertainty market model (Izquierdo et al., 2005) and a trust game model (Abramczuk et al., 2014) to establish an agent-based model. Our approach considers the proportion of honest and false sellers, the reputation of sellers, and the expectation of quality among consumers after purchasing the goods. The results of the study reveal that when false sellers appear in a market with a high degree of quality uncertainty, there is a negative impact on the market, including a decline in consumer expected quality of products in the market, a decrease in commodity transaction volume and market price, and a decrease in seller income. The impact is more pronounced in markets with a higher proportion of false sellers.

However, when consumers’ social and personal learning abilities are higher, and the degree of social network branching is greater, consumers’ ability to exchange information will increase, and the negative impact of false products is reduced. As a result, confidence in the market is increased. The conclusion of this paper is that when consumers have more information and are less impacted by false products, the expected quality will be relatively high, and the income of online e-commerce retailers will be relatively high and stable. Consumers in a market environment where Internet connections are strong and social comparison abilities are relatively high are more able to overcome issues of false products affecting purchasing confidence. In a market environment with low network branching and social learning ability, false goods tend to have a greater negative impact and *vice versa*.

# 1 Introduction

## 1.1 Internet Development and E-commerce Era

Today, e-commerce has become a main component of retail and includes companies such as Amazon, eBay, PChome, Shopee, Open Air, JD.com, Tmall, and Taobao. As online consumption continues to increase, consumers will tend to rely more heavily on information sources such as online information, community opinions, or e-commerce advertisements.

## 1.2 Research motivation and purpose

E-commerce embodies the credit system. The scope of the market is constantly expanding with technology. However, not all consumers can adapt and trust this new market. E-commerce provides a role for middlemen to establish a system of integrity for the online market via information transparency and legal provision of online shopping or auction services, which improves consumers’ trust in online information.

This paper uses an agent-based model to simulate an uncertain market. What will be the effect on the e-commerce market if there are dishonest sellers? This study hopes to explain and contribute to the understanding of the e-commerce market and the behavior of consumers.

## 1.3 Structure of this paper

Section II of this paper contains a literature review on Internet transactions, proxies, social networks, and discussions of e-commerce markets. Section III describes the relationship between the reference model and the parameters, and the experimental design. Section IV discusses and describes the experimental results. Section V summarizes the experimental results, reviews research limitations, and suggests future directions.

# 2 Literature review

# 2.1 Social Learning

Leon Festinger developed the social comparison theory in 1954, which pointed out that everyone makes self-evaluation by referring to the opinions of social groups and using others as a benchmark for comparison (Festinger, 1954).

Albert Bandura pointed out that the key to social learning lies in behavioral changes through observational learning and self-regulation and attention to the interaction between their own behavior and the environment. People can thus learn through social observation, quickly grasping many behavioral patterns and looking for role models for imitation learning, adding learned experience to the decision-making process (Bandura, 1977).

## 2.2 Social networks and the Internet

The concept of a social network can be traced back to 1736, when Euler, a Swiss mathematician, used the concept of a network for mathematical research and proposed graph theory. Euler used a graph to prove that it is impossible to walk all seven bridges without repetition. The term social network was first used by scholar JA Barnes in 1954. He proposed a social structure composed of multiple node connections, where nodes can represent organizations or individuals, and different network connections represent various social relationships. The nodes are connected by one or more specific conditions, and the social meaning of the network is given according to the prevailing conditions.

Due to varying numbers of consumers and the potential for information manipulation to benefit content providers, consumers often encounter content with low credibility on the web (Adam et al., 2014). Therefore, before buying or selling, consumers may refer to the opinions of others or the statistics of commodity data provided by the public on the Internet to judge the quality of commodities and information. Experience increases or decreases the desire to spend.

## 2.3 Interpersonal influence needs

Interpersonal relationships play an important role in needs, work and careers and play a decisive role in the diffusion of information (Granovetter & Soong, 1986). Weaker connections become more frequent with the development of human society and the maturity of network technology.

Janssen and Jager (2001) pointed out that market dynamics and network exchange of information dominate the consumer decision-making process as well as communication with different products in the market and changing consumer behavior. Imitation of other people’s consumption patterns results in product lock-in consumption and trends developing. The unlimited potential of e-commerce development, coupled with the small geographical restrictions, means that the size of e-commerce is increasing.

## 2.4 Collective Intelligence

Hayek (1946) believed that the market economy is a decentralized system of interacting independent agents. Vriend (2002) designed an agent model for independent decision-making and decision-making learning ability in a society that repeatedly provides binary choices under a limited number of consumers through limited choices and continuous experiments, observing the imitation ability of agents. Hayek’s theory provided the idea of evolved learning and adaptive behavior. Through a model that simulates the trustworthiness of Internet content, we investigate how the association between information aggregation behaviors of Internet populations and agents affects the trade-off between “collective intelligence” and “collective stupidity” and the quality of agent decision-making (Abramczuk et al., 2014).

## 2.5 Lemon Market

Akerlof (1978) proposed the idea of lemon markets.[[1]](#footnote-1) In the lemon market, even if someone wants to trade, there may be a market failure due to information asymmetry. In transactions, buyers are only willing to pay the average price because it is difficult to know the quality of the product. Sellers with higher-than-average products suffer losses due to higher costs, while sellers who sell dishonest products benefit from lower costs. Over time, high-quality products gradually withdraw from the market, inferior products fill the market, and the average price drops due to the average quality. Next, consumers will naturally think that the market is full of inferior goods and will only buy them at lower prices. In the e-commerce market, even if consumers have better access to information, they cannot fully grasp the information and real value of products, which results in the lemon market problem.

## 2.6 Market quality uncertainty

When people cannot fully grasp all the information in an e-commerce market due to excessive information and an inability to judge authenticity, people must rely on limited information to ascertain the quality of the market. As consumers attempt to identify a product, knowledge of the product is limited to their own knowledge and experience. When dishonest products appear on the market, the average quality of the product will decline, and the size of the market will be reduced. Even honest sellers or consumers in the marketplace are affected.

When the quality is uncertain, the seller has more information, and if this situation persists, a buyer may doubt the quality of a product or even be reluctant to consume or be satisfied with the sub-optimal product, leading to adverse selection.[[2]](#footnote-2) Consumers lowered their willingness to pay, which made sellers in the market reluctant to offer high-quality goods, and the market shrank until it disappeared.

# 3 Data and Models

This section uses Izquierdo et al. (2005) ’s Market Effects of Quality Uncertainty (MEQU) to simulate different market situations. Various quality expectations, individual comparisons and social comparisons, and the proportion of honest and untrue manufacturers are set in the model, and an agent-based model is established to simulate the interaction between e-commerce and consumers in the online market. This paper uses the MEQU model and refers to the trust game design used by Abramczuk et al. (2014) and Chen & Wang (2017) to set seller agents with different honesty ratios to simulate a market with uncertain quality and consumers’ online influence of the Internet.

## 3.1 MEQU (Market Effects of Quality Uncertainty) Model Introduction

Izquierdo et al. (2005) proposed the MEQU model, arguing that people can learn from experience, use the model to explore the impact of product quality uncertainty on the market, and observe the effect of market information asymmetry on buyers and sellers under different networks.

Table 1. Description of model parameter setting

|  |  |
| --- | --- |
| Symbol | Parameter Name |
| Seller agents |
| *ns* | Number of Sellers |
| $$sp\_{i}$$ | Selling price |
| $$msp\_{i}$$ | Lowest selling price |
| Strategy | Seller strategy: (honest) / (dishonest) |
| Rating | Seller’s reputation |
| Buyer agents |
| *nb* | Number of Buyers |
| $$R\_{i}$$ | Reservation price |
| $$q\_{i}$$ | Expected quality |
| $$SR\_{i}$$ | Standard reservation price |
| $$q\_{i,n}$$ | The total expected quality of the buyer’s agent in each period |
| $$\hat{q}\_{i,n}$$ | Buyer agent i’s current (n) expected quality |
| $$λ\_{ind}$$ | Individual comparison weight |
| $$λ\_{soc}$$ | Social comparison weight |
| *F* | The expected quality variable after the purchase of goods is deceived, which is set to 0.05 in this paper |
| Market parameters  |
| $$i$$ | Index of agents |
| $$p\_{n}$$ | Market price |
| $$\overbar{q}\_{i, n}$$ | Market average expected quality |
| $$y$$ | Number of transactions |
| Links | Number of social network connections |

In the MEQU model, it is assumed that buyers learn from the experience of others through the links on the Internet and form views on the expected quality of the product based on past direct experience and that of others. In the model, each seller generates a sales price $sp\_{i} $=($i=1,2…$*ns* ). The seller’s lowest selling price is$ msp\_{i}=i$. In each trading session, the seller can sell at most one commodity. If the market price (p) is not less than the seller’s lowest willingness to sell price $(p\geq msp\_{i})$, then there will be a supply in the market.

Each buyer generates a reservation price $(R\_{i})$ and an expected quality, ($\hat{q}\_{i,n}$) and will multiply its reservation price $(R\_{i,n})$ by the nth transaction round. The expected quality $\hat{q}\_{i,n} $of n rounds, forming the standard reservation price $(SR\_{i})$ and the reservation price of each agent is arranged by $(i=1,2,…,n\_{b} )$to form a standard reservation price$(SR\_{i}=i).$During the simulation process, the standard reservation price of each buyer $(SR\_{i}) $will remain unchanged at the beginning. When the buyer’s initial expected quality ($\hat{q}\_{i,0}$) is 1, each buyer’s initial reservation price $(R\_{i,0}) $is equal to a standard reservation price$ (SR\_{i})$, until the buyer’s expected quality ($\hat{q}\_{i,n}$) is updated. At any trading round, the individual reservation prices for *nb* buyers will be ranked as follows:

$R\_{1,n}\geq R\_{2,n}\geq \cdots \geq R\_{n\_{b}, n} $  (1)

The initial demand price is $[0<p\leq n\_{b}]$ and the demand quantity is $[n\_{b}+1-p]$. In each transaction, buyers will receive new products, they will update the expected quality ($q\_{i}$) due to the quality of the purchased products, and the standard reservation price $(SR\_{i})$will vary with the buyer’s expected quality ($\hat{q}\_{i,n}$) changes, so the demand function changes accordingly.

In each transaction, the buyer can buy at most one commodity, while the seller can sell one commodity, and the transaction will be completed at the equilibrium point of supply and demand every *n* rounds. The formula for the market price is as follows:

$p\_{n}= \frac{1}{2} [Min(SR\_{y,n}, msp\_{y+1})+ Max(SR\_{y+1,n}, msp\_{y})$] (2)

In each round of transactions, the maximum number of transactions $y$ is equal to the maximum value of $i$, for example $[SR\_{i,n}\geq msp\_{i}] Buyer’s$ reservation price $(R\_{i,n})$

$ g$reater than or equal to the willingness to sell price ($msp\_{i})$.

In the simulation process, buyers update their expected quality after each transaction, and when buyers update their individual expected quality, they are mainly determined by social-weight and individual-weight.

When a buyer’s social weight $(λ\_{soc})$ is larger, the buyer will attach more importance to and experience, and when the buyer’s individual weight $(λ\_{ind})$ is higher, they will consider their experience more. When each transaction round passes, consumers will update their quality expectations by multiplying the individual reservation price by the expected quality ($q\_{i,n}$) of the product in the current period. Each consumer’s initial expected quality $\left(q\_{i,0}\right) $is 1.

Each consumer will use the social weight $(λ\_{soc})$ and the individual weight$(λ\_{ind})$ as the sensitivity to online information. If the social weight $(λ\_{soc})$ is higher, the consumer will rely more heavily on opinions in the online community. If the individual weight $(λ\_{ind})$ is higher, consumers will consider their past experience more to form ($q\_{i,n}$) expected quality. In addition,$ (\overbar{q}\_{i, n})$ is the market average expected quality, while$ (\hat{q}\_{i,n})$ is the expected quality produced by each buyer in the current period.

Individual and Social Comparison Comprehensive:

$\hat{q}\_{i,n+1}= \hat{q}\_{i,n}+λ\_{ind}\left(q\_{i,n}-\hat{q}\_{i,n}\right)+λ\_{soc}(\overbar{q}\_{i, n}-\hat{q}\_{i,n})$(3)

When a buyer buys a product, but there is no link on the network to which it is connected ($λ\_{soc}=0$) :

$\hat{q}\_{i,n+1}=\hat{q}\_{i,n}+λ\_{ind}\left(q\_{i,n}-\hat{q}\_{i,n}\right)$(4)

When the buyer does not purchase the product ($λ\_{ind}=0$) but has a link on the connected network and has purchased it:

$\hat{q}\_{i,n+1}=\hat{q}\_{i,n}+λ\_{soc}(\overbar{q}\_{i, n}-\hat{q}\_{i,n})$(5)

The weight ratio in the model is set as $λ\_{ind}\geq 0$ ，$ λ\_{soc}\leq 1$. When the $λ\_{ind}$ value and the number of social network connections in the market are 0, the market quality will not change. When $λ\_{ind}$ is 0, consumers have no individual learning effect; when the number of social network connections is 0, consumers cannot exchange information with each other. Therefore, consumers’ expected quality will not change, and all results will remain equivalent to those produced by the initial conditions. Section IV describes the weight variable settings used in this paper.

In Figure 1, the commodity quality (*q*) parameter of the market in the MEQU model has three different distribution modes: Exponential Distribution, Uniform Distribution, and Trimmed Normal Distribution. The commodity quality *q* follows a predetermined fixed mass distribution. This experiment adopts the exponential distribution and assumes that the expected value of the quality E(*q*) of each commodity is equal to 1.

 

Figure 1 Operation interface of this study

## 3.2 Model Design

This study relies on the trust game model (Abramczuk et al., 2014) to add reputation variables and capture honesty strategies by sellers. Buyer adjustments to expected quality ($q\_{i,n}$) made after purchasing the item are simulated. In the face of dishonest sellers, we investigate whether consumers are affected by dishonest sellers in terms of market prices, transaction volumes, and seller earnings.

There are two kinds of agents in the agent-based model of this paper, consumers (buyers) and e-commerce sellers (See Figures 2 and 3). Referring to the game modeling method of Abramczuk et al. (2014), the seller’s honest strategy is added to the MEQU model. When the buyer purchases the product, when the buyer’s $λ\_{ind}$value and the number of social network connections are both greater than 0, the buyer will update the personal reservation price$ (SR\_{i,n})$ and the expected quality ($q\_{i,n}$). In this study, 100 buyer agents and 100 seller agents are modeled, and the social network is modeled as a random network. When the number of network connections is 200, 100 buyers are connected to an average of 2 buyers on the network, and when the number of network connections is 1000, they are connected to an average of 10 buyers. Buyers linked through this manner can exchange opinions with each other.

Start

Generate $n\_{b}$ buyer's agents and reservation prices $(R\_{i,0})$ and initial expected qualities $(\hat{q}\_{i,0})$.

Agents connect with each other and update their reseration prices and expected qualities

$$SR\_{i,n+1}-R\_{i}(\hat{q}\_{i,n+1})$$

Expected quality is determined by a combination of social comparison weights and personal comparison weights

$$\hat{q}\_{i,n+1}-\hat{q}\_{i,n}+λ\_{ind}(q\_{i,n}-\hat{q}\_{i,n})+λ\_{soc}(q\_{i,n}-\hat{q}\_{i,n})$$

Transaction if

$$[SR\_{i,n}\geq p\_{n}]$$

Do not trade and wait for the next round of transaction

Trade

Buy Strategy = false

 $\hat{q}\_{i,n+1}×F$

Buy Strategy = true

 $\hat{q}\_{i,n+1}$

Trading rounds greater than 500 rounds

End

NO

YES

YES

NO

Figure 2. The formation process of buyer agents

The buyer agent learns the quality (q) information of the new commodity by purchasing it in the market. When the buyer’s expected quality after purchase $(q\_{i,n})$ is higher, the chance of purchasing new products is higher. When the buyer buys a false product in the market, the post-purchase expected quality $(q\_{i,n})$ will decrease. The expected quality of the updated product after the buyer is deceived is $(q\_{i,n})×F$. We set *F* as 0.05, simulating a loss of trust in the seller after being deceived. In each transaction round, the buyer will select the commodity whose reserved price $(SR\_{i})$ is prioritized in the market, but there may still be honest or dishonest sellers in the market at the same time.

Start

Honest = false

Random sales real or fake

(Strategy= true/false)

One seller agent is randomly selected to view the market

each time Rating＞itself Rating follow the former strategy

Generate *ns* seller agents, follow *ns* ($i=1,2…$*ns* ) Generate the lowest willing selling price

Honest = true

Sell real product

(Stretagy= true)

$$p\_{n}\geq msp\_{i,n}$$

No item sold

buy real products (Rating+1)

sell fake goods (Rating-1)，Add a deal with a deal

More than 500 trading rounds

End

No

Yes

yes

No

No

Yes

Honest?

Figure 3. The formation process of seller agents

The honest ratios among the 100 sellers in this study are 100%, 80%, 50%, and 20%, respectively, corresponding to 100, 80, 50, and 20 honest sellers, with the remaining share being dishonest sellers. A reputation mechanism, as used by Abramczuk et al. (2014), is added to record the seller’s evaluation of the buyer’s agent in the market.

When a buyer buys an inauthentic product, the seller posts a negative review and writes it into its reputation record. On the contrary, if the buyer buys a real product, a positive review record will be added to the seller. The law of imitation and learning among sellers, when the seller’s agent finds that the reputation of the seller’s agent that he chooses to view is better than herself, the seller’s agent will follow the strategy of the seller’s agent he checked in this round. For example, when the seller’s agent chooses to refer an honest seller, if the seller’s reputation is higher than herself, she will choose to be an honest seller. When the seller’s agent chooses to refer a dishonest seller, if the seller’s reputation is higher than herself, she will choose to be an dishonest seller.

## 3.3 Experimental Design

In this paper, four groups of experiments were performed, and each group of experimental parameters was repeated 20 times, with 500 ticks each time. There were 100 buyers and 100 sellers’ agents. Whether the seller’s agents were honest, the number of network connections of the buyer’s agent, the social comparison weight, and the individual comparison weight were set at the outset. Observed changes in market commodity volume, market prices, sellers’ income, and buyers’ average expected quality was also set at the outset. The experimental parameters are as follows:

Social weight $[λ\_{soc}$ =0.2, 0.4], individual weight [$λ\_{ind}$=0.2, 0.4], number of links [links=0 , 200 , 400 , 800 , 1000 ], individual weight [$λ\_{ind}$=0 , 0.01, 0.05 , 0.1 , 0.2 , 0.3 , 0.4 , 0.5 , 0.6 ] with different honest seller ratios [20%, 50%, 80%, 100%].

The average value of the transaction results of the last round of the 20 simulated markets was compared, and the influence of dishonest sellers on the e-commerce market was observed.

# 4 Simulation results and analysis

In this section, the changes in commodity transaction volume, market price, seller’s income, and buyer’s average expected quality are organized into tables.

## 4.1 The time tendency of the fundamental market

Buyers in the market can use the ability of individual learning to yield improvements when purchasing new products.

Its expected quality, Figure 4, reflects the changes in the market trend of commodity volume, market price, seller’s income, and buyer’s average expected quality with the increase of transaction rounds when there are honest sellers in the market.

Figure 4. Line chart of market transaction status of 100% honest sellers at λind=0.2, λsoc=0, Links=0

The results in Figure 4 show that the decline in transaction volume and price reflects the decrease in buyer demand and sellers’ income under saturated market conditions, which is consistent with the results of Izquierdo et al. (2005).

When dishonest sellers appear in the market, if buyers do not have a social network, they soon lose confidence in the products on the market. The quality declines rapidly, and as the trading time goes on and the market may even shrink to the point at which trading stops, resulting in market failure. In other experiments, the result of this market failure is that with the addition of social learning and social network connectivity, the negative impacts of quality uncertainty brought about by individual learning begin to decrease and are presented in subsequent experimental results.

## 4.2 Simulation result verification

In this paper, the 100% honest seller market is used as the benchmark, and the 80%, 50%, and 20% honest seller markets are used for independent sample t-tests. From Tables 2 to 5, the p-values in the experimental results of each group are almost all significant, reflecting the existence of dishonest sellers. Significant negative impact on the market.

Table 2. t-test for different honest ratio markets with social weight $λ\_{soc}$=0.2

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| The percentage of honest sellers | Variable | Average | Standard deviation | *t* Value | *P* Value |
| 80% | Traded volume | 30.26 | 14.36 | 16.384 | .000\*\*\* |
| Market price | 30.78 | 14.30 | 16.496 | .000\*\*\* |
| Seller’s income | 560.62 | 342.30 | 17.643 | .353 |
| Buyer’s average expected quality | 0.67 | 0.29 | 19.681 | .000\*\*\* |
| 50% | Traded volume | 26.66 | 13.58 | 23.366 | .000\*\*\* |
| Market price | 27.18 | 13.56 | 23.495 | .000\*\*\* |
| Seller’s income | 447.63 | 289.38 | 26.594 | .000\*\*\* |
| Buyer’s average expected quality | 0.59 | 0.28 | 28.058 | .000\*\*\* |
| 20% | Traded volume | 24.28 | 12.83 | 28.612 | .000\*\*\* |
| Market price | 24.80 | 12.81 | 28.745 | .000\*\*\* |
| Seller’s income | 377.07 | 254.43 | 32.895 | .000\*\*\* |
| Buyer’s average expected quality | 0.54 | 0.27 | 34.056 | .000\*\*\* |
| \*p<0.05,\*\*p<0.01,\*\*\*p<0.001 |

Table 3. t-test for different honest ratio markets with social weight $λ\_{soc}$=0.4

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| The percentage of honest sellers | Variable | Average | Standard deviation  | *t* value | *P* value |
| 80% | Traded volume | 32.99 | 14.58 | 11.697 | .000\*\*\* |
| Market price | 33.51 | 14.60 | 11.765 | .000\*\*\* |
| Seller’s income | 651.38 | 381.39 | 11.464 | .000\*\*\* |
| Buyer’s average expected quality | 0.73 | 0.29 | 14.389 | .000\*\*\* |
| 50% | Traded volume | 31 | 14.82 | 14.921 | .000\*\*\* |
| Market price | 31.55 | 14.78 | 14.990 | .000\*\*\* |
| Seller’s income | 591.05 | 360.06 | 15.535 | .000\*\*\* |
| Buyer’s average expected quality | 0.69 | 0.30 | 17.769 | .000\*\*\* |
| 20% | Traded volume | 29.56 | 14.68 | 17.467 | .000\*\*\* |
| Market price | 30.07 | 14.66 | 17.591 | .000\*\*\* |
| Seller’s income | 544.45 | 343.04 | 18.869 | .002\*\* |
| Buyer’s average expected quality | 0.65 | 0.30 | 20.983 | .000\*\*\* |
| \*p<0.05,\*\*p<0.01,\*\*\*p<0.001 |

Table 4. t-test for different honest ratio markets with individual weight $λ\_{ind}$=0.2

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| The percentage of honest sellers | Variable | Average | Standard Deviation | *t* value | *P* value |
| 80% | Traded volume | 26.28 | 15.84 | 18.699 | .000\*\*\* |
| Market price | 26.85 | 15.75 | 18.846 | .000\*\*\* |
| Seller’s income | 470.96 | 386.91 | 16.036 | .000\*\*\* |
| Buyer’s average expected quality | 0.6 | 0.32 | 25.659 | .000\*\*\* |
| 50% | Traded volume | 23.15 | 15.6 | 24.337 | .000\*\*\* |
| Market price | 23.72 | 15.53 | 24.488 | .000\*\*\* |
| Seller’s income | 389.96 | 356.92 | 22.239 | .000\*\*\* |
| Buyer’s average expected quality | 0.53 | 0.32 | 32.279 | .000\*\*\* |
| 20% | Traded volume | 21.17 | 15.29 | 28.184 | .000\*\*\* |
| Market price | 21.76 | 15.21 | 28.363 | .000\*\*\* |
| Seller’s income | 341.39 | 337.12 | 26.346 | .000\*\*\* |
| Buyer’s average expected quality | 0.48 | 0.32 | 37.149 | .000\*\*\* |
| \*p<0.05,\*\*p<0.01,\*\*\*p<0.001 |

Table 5. t-test for different honest ratio markets with individual weight $λ\_{ind}$=0.4

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| The percentage of honest sellers | Variable | Average | Standard Deviation | t value | *P value* |
| 80% | Traded volume | 25.77 | 14.40 | 8.685  | .000\*\*\* |
| Market price | 26.34 | 14.31 | 8.735 | .000\*\*\* |
| Seller’s income | 436.07 | 347.09 | 6.138 | .000\*\*\* |
| Buyer’s average expected quality | 0.62 | 0.29 | 13.520 | .000\*\*\* |
| 50% | Traded volume | 23.61 | 14.9 | 12.041 | .000\*\*\* |
| Market price | 24.17 | 14.86 | 12.133 | .000\*\*\* |
| Seller’s income | 390.26 | 344.17 | 9.139 | .000\*\*\* |
| Buyer’s average expected quality | 0.56 | 0.31 | 18.353 | .000\*\*\* |
| 20% | Traded volume | 22.18 | 14.84 | 14.474 | .000\*\*\* |
| Market price | 22.75 | 14.76 | 14.563 | .000\*\*\* |
| Seller’s income | 356.22 | 330.32 | 11.603 | .036\* |
| Buyer’s average expected quality | 0.53 | 0.32 | 20.907 | .000\*\*\* |
| \*p<0.05,\*\*p<0.01,\*\*\*p<0.001 |

Table 6. Regression of social weight, individual weight, initial honesty ratio,

and the number of connections to the honesty ratio at the 500th round

OLS, using observations 1-1440

Dependent variable: final\_ratio

Heteroskedasticity-robust standard errors, variant HC1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *Variable*  | *Coefficient* | *Std. Error* | *t-ratio* | *p-value* |  |
| λsoc | 40.6782 | 5.18098 | 7.851 | <0.0001 | \*\*\* |
| λind | 40.6503 | 5.18269 | 7.843 | <0.0001 | \*\*\* |
| inital\_ratio | 0.275484 | 0.0288071 | 9.563 | <0.0001 | \*\*\* |
| links | 0.014121 | 0.0024897 | 5.672 | <0.0001 | \*\*\* |
| Mean dependent var |  50.00646 |  | S.D. dependent var |  36.24076 |
| Sum squared resid |  2181851 |  | S.E. of regression |  38.97942 |
| R-squared |  0.602643 |  | Adjusted R-squared |  0.601812 |
| F(4, 1436) |  541.9301 |  | P-value(F) |  5.3e-285 |
| Log-likelihood | −7316.037 |  | Akaike criterion |  14640.07 |
| Schwarz criterion |  14661.16 |  | Hannan-Quinn |  14647.95 |

## 4.3 Effect of market parameters on results

The results of price and commodity trading volumes were obtained after 500 transactions in each market. When the market is full of honest sellers, with the increase in the number of network connections and the individual comparison weight $λ\_{ind}$, the sales volume and price of the product decrease steadily. With a lower number of connections, the higher the decline. Izquierdo et al. (2005) showed that when the social weight $λ\_{soc}$ is lower and the individual weight $λ\_{ind}$ is higher, buyers rely more on individual experience to generate expected quality. In this case, buyers generally underestimate the actual quality of goods, and the willingness to pay decreases. When dishonest sellers begin to appear in the market, the number of Internet connections falls, as does sales volume. Some buyers buy false goods in the market, which greatly reduces the expected quality, and the price of the goods in the market also falls. When there are fake sellers in the market, there are a higher number of Internet connections. The higher the market price and commodity transaction volumes, the weaker the impact of fake products as buyers will share more information due to the connection, and the less they will be attacked by fake products. Confidence in market commodities is less likely to underestimate the expected quality of commodities. However, when the proportion of dishonest sellers is higher, the negative impact on market price and sales volume is more obvious.

The observation results show that the higher the buyer’s network connection and the social comparison weight $λ\_{soc}$, the higher the seller’s income, whether in a completely honest market or a market containing dishonest sellers. When buyers can obtain more information, the lower the impact of fake goods on buyers’ expected quality in the market. The higher the seller’s income, the less than honest sellers are affected by the “lemon problem” in this market.

The average expected quality results of buyers after 500 transactions in each market under the fixed $λ\_{ind}$ =0.2 of the individual comparison weight condition. Whether in a completely honest market or a market with dishonest sellers, as the number of Internet connections increases and the social comparison weight $λ\_{soc}$ increases, the average expected quality of buyers will be higher and higher, and the social comparison weight $λ\_{soc}$ becomes lower. At 0.4 and the number of Internet connections is less than 400, the market will be badly affected by fake products, and the average buyer’s expected quality is thereby significantly reduced. It is easy to be influenced by inferior goods brought by fake goods to drive out high-quality goods.

# 5 Conclusions and future research suggestions

## 5.1 Conclusion

By adding the attributes of honesty and dishonesty to the seller’s agent in the MEQU model and adding dishonesty products to the market, changes in the expected quality ($q\_{i,n}$) among consumers are modeled, and changes in consumers’ mentality after being deceived is moderated.

This paper makes a summary of the experimental results. Through the experiment, we find that when consumers have social connections, the higher the social comparison weight $λ\_{soc}$, they are more willing to accept the opinions of other buyers in the market, and the expected quality is higher, objective, stable, and ultimately less affected by fake sellers. From the experimental results, it can be observed that the higher the social comparison weight $λ\_{soc}$ and the higher the number of network connections, the more stable the market transaction results, prices, and sellers’ income. Under such market conditions, through news dissemination and information sharing, a stable expected quality among consumers ($q\_{i,n}$) and emerges and *vice versa.* When the number of Internet connections is low, the transaction results and prices of the market and the income of sellers gradually decrease, and the destructive effect of fake products is stronger.

At the same time, when the consumer’s individual comparison weight λ is higher, the consumer’s individual learning ability is correspondingly improved, but in a market with uncertain quality, depending on the quality of the market, this may impact the consumer’s expected quality ($q\_{i,n}$). If an individual comparison weight $λ\_{ind}$is higher, and the social comparison weight $λ\_{soc}$ is lower, it is likely to have an extreme reaction to the market. From the experimental results 4.2 and 4.3, it can be found that, for example, there are false purchases. From then on, would-be buyers may think that the quality of the products is unreliable and therefore refuse to buy the products, and the originally good e-commerce companies in this market may withdraw from the market due to the size of the market diminishing.

The above market results are generally like the results of the “lemon market.” When false products appear in the market, a defective market is formed, causing consumers to refuse to make purchases. With the increase in the degree of connection and the improvement in the ability to grasp information, consumers are better able to independently judge expected quality, and because of the existence of false products in the market, they will not refuse to re-enter the market. At the same time, because of the exchange of information, the idea that the whole market is inferior goods is broken, and the individual cognitive bias is corrected by the influence of information exchange. In this experiment, consumers are better able to observe and grasp information from others. This phenomenon can also be found in a market with higher social comparison, individual learning ability, and social connections. In such a market, consumers have higher quality expectations, and online e-commerce income is higher and more stable.

However, when e-commerce is facing the online market, the average quality of the entire commodity market will be affected by these fake commodities, and consumers will therefore lose confidence in commodities and their expected quality ($q\_{i,n}$) will decline. This phenomenon has been observed through simulation experiments: the greater the uncertainty of quality, the lower the number of network connections, and the lower the ability for consumers to learn and compare, the weaker the e-commerce market. When e-commerce faces a market with many dishonest sellers, it will suffer losses due to the extreme negative expectations of consumers. The market space may even shrink until it no longer exists.

Therefore, for e-commerce to be successful, consumers must trust the online market. It is possible for consumers to fail or even destroy the market due to false goods or information that overestimate the quality of goods in the market. Only when information is shared and disseminated on social networks are consumers with low expectations more likely to change their views, reducing the occurrence of adverse consumer selection in the market.

# References

1. Akerlof, G. A. (1978). The market for “lemons”: Quality uncertainty and the market mechanism. In *Uncertainty in Economics* (pp. 235-251)
2. Bandura, A., & Walters, R. H. (1977). Social learning theory (Vol. 1). *Englewood Cliffs, NJ: Prentice-hall*.
3. Festinger, L. (1954). A theory of social comparison processes. *Human relations*, 7(2), 117-140.
4. Granovetter, M., & Soong, R. (1986). Threshold models of interpersonal effects in consumer demand. *Journal of Economic Behavior & Organization, 7*(1), 83-99.
5. Hayek, F. A. (1946). Individualism, True and False: The Twelfth Finlay Lecture Delivered at University College, Dublin, on December 17, 1945. Hodges, Figgis.
6. Izquierdo, S. S., & Izquierdo, L. R. (2007). The impact of quality uncertainty without asymmetric information on market efficiency. Journal of Business Research, 60(8), 858-867.
7. Janssen, M. A., & Jager, W. (2001). Fashions, habits and changing preferences: Simulation of psychological factors affecting market dynamics. Journal of economic psychology, 22(6), 745-772.
8. Kreps, D. M., & Wilson, R. (1982). Reputation and imperfect information. Journal of economic theory, 27(2), 253-279.
9. Papaioannou, T. G., Aberer, K., Abramczuk, K., Adamska, P., & Wierzbicki, A. (2012, April). Game-theoretic models of web credibility. In Proceedings of the 2nd Joint WICOW/AIRWeb Workshop on Web Quality (pp. 27-34). ACM.
10. Travers, J., & Milgram, S. (1967). The small world problem. Phychology Today, 1(1), 61-67.
11. Vriend, N. J. (2002). Was Hayek an ace?. Southern Economic Journal, 811-840.
12. Watts, D. J. (2004). Six degrees: The science of a connected age. WW Norton & Company
13. Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. nature, 393(6684), 440.
14. Wierzbicki, A., Adamska, P., Abramczuk, K., Papaioannou, T., Aberer, K., & Rejmund, E. (2014). Studying web content credibility by social simulation. Journal of Artificial Societies and Social Simulation, 17(3), 6.
15. Yu, T., Chen, S. H., & Wang, C. H. (2017, June). Information Aggregation in Big Data: Wisdom of Crowds or Stupidity of Herds. In International Symposium on Distributed Computing and Artificial Intelligence (pp. 16-27). Springer, Cham
1. "Lemon" is "defective" or "defective" in American slang. [↑](#footnote-ref-1)
2. The "lemon problem" refers to the fact that sellers can use information asymmetry to deceive buyers, which hides information and leads to adverse selection of consumers. [↑](#footnote-ref-2)