Effects of Information and Country of Origin on Chinese Consumer Preferences for Wine: An Experimental Approach in the Field

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1. Introduction

With one of the world's most rapidly growing economies, the largest population over 1.3 billion and relatively low level of per capita annual income under USD2000, China has become a large potential market for consumption goods, especially for food products. According to the China Statistical Yearbook 2008, China's GDP had achieved 24.95 trillion Yuan (3.56 trillion USD: based on the approximate exchange rate 1USD=7 Yuan; hereinafter inclusive) at the end of 2007. More importantly, China has shown an amazing 10 percent annual increase in the economy in the last two decades. Furthermore, the per capita disposable incomes for urban and rural residents in China were 13786 Yuan and 4140 Yuan, respectively, as of 2007, both of which showed a 7 percent annual increase since 1979. Even though it is argued that China's living standards are at relatively low level compared to most developed economies, there would nevertheless be considerable latitude for food consumption in the light of these growth expectations.

Another reason why the Chinese market for food is expected to grow rapidly is the high Engel coefficient of Chinese households. For urban households, the Engel coefficient is 36.3 percent in 2007, while it is 43.1 percent for rural households. Although these numbers have dropped dramatically since 1979, they are still at a higher level compared to those of developed countries, such as the US (13.74 percent in 2005), Great Britain (17 in 2007), Japan (23.49 percent in 2007) and Germany (20 percent in 2007). Domestic per capita food consumption is rising slightly over time, but the trends differ by urban and rural areas. The urban residents increased their average food consumption from 2914 Yuan in 2005 to 3112 Yuan in 2006 and 3628 Yuan in 2007. On the other hand, the per capita food consumption of rural residents increased from 1162 Yuan in 2005 to 1217 Yuan in 2006 and 1389 Yuan in 2007.

In general, the food consumption in China is rising. In a considerably long period, food consumption would still play an important role in the Chinese households. There is rising demand for quantity due to the rising household income, however, it is not only the quantity but also the quality of which the demand is rising in China. Nowadays, people want to consume food products which are healthier, more nutritious, and even more stylish. Take the urban residents in 2007 as an example, and we notice that only 7.7 percent of per capita food consumption goes to the staple food, such as grains, rice, and corn, which implies that urban residents tend to spend more money on non-staple food, such as meat, eggs, and dairy products, etc. On the other hand, with the fast pace of globalization and China's entry to WTO, more foreign products are available in Chinese market, and people are willing to try new food products from the western world other than traditional Chinese food. Wine is one of these products.

China is a newcomer and latecomer to wine production and consumption. The wine production began to arise only in the late 1980s, but has grown rapidly in recent years. Compared to the traditional Chinese hard distilled liquor, wine production and consumption remain at low levels. In 2003, China produced 350,000 tons of wine, but that only accounted for about 1 percent of the country's total alcohol production (Huang, et al., 2009). As for wine consumption, per capita wine consumption in China is only 0.3 liters as of 2005, which is much lower than the numbers of the US (12 liters), Japan (3 liters) and France (59 liters) (GAIN Report CH6809, 2006). However, the urban residents show greater interest in consuming wine products that their average consumption of wine in 2005 is approximately 1 liter. Wine consumption, especially imported wine, rarely exists outside of major urban areas. Therefore, we can see an enormous potential for wine consumption in China, especially in major urban areas. There are three primary reasons: first, urban residents are more likely to have higher disposable income, so they might stand a greater chance to consume high quality products; second, it is easier for urban residents to see and purchase wine products; third, most of the existing wine consumers are living in the urban areas.

Most of the demand for wine is satisfied by domestic wine producers, such as the Great Wall and Dragon Seal. Even though the domestic wine products do not hold a good reputation, the overall quality has been improved in the past years. Imported wine products can also be easily found in supermarkets, upscale hotels, and restaurants, still the market share of imported wine remains at a low level. Chinese wine imports in 2003 constituted slightly more than 12 percent of domestic production (Huang et al, 2009). As we discussed earlier, it is expected that there is good opportunity for imported wine products. However, understanding the local markets and consumer preference for wine products is important for foreign wine producers.

Willingness-to-pay (WTP) is the maximum amount a person would be willing to pay or exchange for a good. There are several methods available to estimate consumer WTP for novel goods or changes in the qualities of existing goods, such as Dichotomous Choice Questions, Choice-based Conjoint Analysis, and Experimental Auctions (Lusk and Hudson, 2004). Experimental auctions are becoming a popular method to elicit consumer WTP because evidence that consumers respond differently in hypothetical and real environments.

The main objective of this article is to elicit the WTP of both student and resident consumers in Beijing and Shanghai for four different wine products which are originated in China, France, USA, and Australia, respectively, by using a second-price sealed-bid auction mechanism that was first developed by Vickrey (1961). Furthermore, the paper will also examine how the WTP elicited are affected by some socio-demographic factors. The rest of this paper will be organized as follows. We first describe our experimental auction method and data collected through the auction process in Section 2. Section 3 discusses an empirical model used to analyze the data, and the results are presented. In Section 4, we draw some concluding remarks.

2. Method and Data

2.1 Second-price Sealed-bid Auction

There are several advantages and drawbacks of using experimental auction to elicit consumer WTP for novel goods or services However, some of these drawbacks can be mitigated by conducting experiments in a field rather than lab setting (Lusk and Hudson, 2004).

Some studies focus on the effects of different auction mechanisms on the elicited consumer WTP. Lusk, Feldkamp, and Schroeder (2004) investigate the effect of several procedural issues on valuation estimates from experimental auctions. Their results indicate the second price auction generates higher valuations than English, BDM and random *n*th price auctions, especially in latter bidding rounds, and that random *n*th price auction yields lower valuations than English and BDM. Perry and Reny (2002) give some new insights and comments on and efficient auction, developed by Vickrey (1961). Their interest lies in modifying Vickrey's auction so that efficiency does obtain even when the bidders' values are interdependent, while maintaining Vickrey's assumptions that the goods for sale are homogeneous and that each bidder's demand is downward sloping. Lusk, et al. (2000) conducted both first-price and second-price auctions for corn chips made with non-genetically modified ingredients to elicit consumer WTP. Results suggest that the second-price auction induces a greater percentage of marginal bidders to offer a positive bid than first-price auction. However, their results also indicate that average bid levels in the 1st and 2nd price auctions were not statistically different from one other. Shogren, et al. (2001) evaluate how three auction mechanisms – BDM, the second-price auction, and the random *n*th-price auction – affect the measurement of WTP and WTA measures of value. Their experiments show that while initial bidding behavior does not contradict the endowment effect concept, the effect can be eliminated with the repetitions of a second-price or random *n*th-price auction. Their findings also suggest that auction mechanism itself can account for the conflicting observations in Kahneman et al. (1990) and Shogren et al. (1994a).

In our study, a second-price sealed-bid multi-round auction mechanism is selected. And the experimental design is described as follows.

2.1.1 Organization

Beijing and Shanghai are the two largest cities in China, and are always considered to be major markets for western foods, including wine products. Considered as a healthier alternative to the traditional Chinese liquor, wine products are widely provided in supermarkets, liquor stores, hotels, and restaurants, etc. So, our study focuses on two cities, Beijing and Shanghai.

The experimental auction covered a five-week period from May 11th to June 7th, 2009, and all of the auctions were conducted on the weekends. This is because people who stay at home during the daytime of week days are mostly senior or unemployed, which would generate sampling bias in the structure of participants. The participants included college students from three major universities and residents from seven communities in Beijing and Shanghai.

It is noted that this experiment is a field experiment, which is different from the one conducted in the laboratory, and the circumstances are complicated and difficult to control. Moreover, except for college students, the resident participants were showing a significant difference in ages and education levels.

In addition, 10 college students were hired and trained as assistants during the auction process. They helped the auctioneer maintain order, collect sealed bids from participants, and collect the questionnaires.

2.1.2 Experimental Subjects

All the participants in this experimental auction were recruited from 7 randomly chosen communities and 3 major universities in Beijing and Shanghai. The total number of participants is 423, in which 195 are residents and 228 are students.

For the students, they signed up for the experimental auction through an online registration system, which has been established by the three universities for economic experiment recruitment. They could sign up for the time period which was appropriate for them, with the limit of 30 participants per time period, so totally we had 9 different time periods for students. After students gathering in each time period in the one classroom, the students were randomly divided into two small groups.

For the residents, the recruitment was more difficult and complicated. We first contacted the community offices and asked help from the staff in the office. Having received the permission from the community offices, we put up advertisements of recruitment in the community where the advertisement was open to public. Once the residents saw the ad and were interested in the experimental auction, they could stop by the community office and sign up for the appropriate time period. Since we could only find one meeting room in each community, each two consecutive time periods would be considered as a pair wise comparison group, just as the two groups in the same time period for the students. As we had expected, the size of groups varied from 10 to 15, since some participants did not show up. Each participant received a 30 Yuan (Chinese currency) show-up award for taking part in the experimental auction.

For a pairwise comparison group, one of the two groups would take part in the auction with information exposure while the other without information. Before the auction started, the auctioneer would read the experiment instructions and simulated how the bidding process would proceed. If no questions were asked, the auction got started.

2.1.3 Items for Auction

The items for auction are four bottles of wine from 4 different origins (France, Australia, U.S., and China). The wine products are described in Table 2.1. To make the results comparable, we used the same four wine products across all the groups. The wine was purchased at the Carrefour Supermarkets in both Beijing and Shanghai. When they were displayed at the auctions, each bottle had a label indicating the origin of production. During the auction process, the participants were free to hold the wine in his/her hands and inspect the labels for the corresponding products. Discussion and talking were strictly prohibited during the auction, so that the participants would not be influenced by each other and make their own decisions.

2.1.4 Multi-round Auction without Information exposure

Firstly, we will do auction **without** information exposure for one group. The subjects only understand that the items they are going to bid for are wines from different origins, however, the auctioneer do NOT in detail give any introduction to what the differences between them. All the participants in each group will be given three offer sheets.

Each subject can only look at their own offer sheets, bidding (both price and quantity) for the four bottles of wine all by themselves. To avoid collusion, talking with other participants is strictly prohibited during the auction procedure. As for the offer sheet, the quantity is either zero or one, and the price must be greater than zero (accuracy RMB 1 Yuan).

All bidders submit the price and quantity for the first round. The bidding price for the first round cannot be zero because we need our experiment to reflect consumers' different preferences over the four bottles of wine, i.e. the bidding price difference must be identified even at lower prices. The concern is that some bidders will be likely just to take the 30 Yuan show-up award and not participate in the auction procedure. Then, the auctioneer announces the highest prices for all of the items, and this highest price from the first round will be the starting prices for the second round. Then at the end of the second round, the auctioneer announces the highest prices for all of the items. Similar to the first round, the highest prices for the second round will be the starting prices for the third round. And then we go for the third round. Here we only do a three-round auction.

In the second and third rounds, the participants may choose to offer zero bids. If one has offered zero bids in the second round, he can still offer greater-than-zero bids in the third round, but these bids should be based on the highest bids from the second round. And the participants may also choose to offer zero bids for some of or all of the wine products.

Finally, the bidder offering the highest price wins the auction, but this bidder will only buy the item he won in auction at the second highest price, i.e. second price auction. For example, the highest three bidding prices for the wine from China are RMB50, RMB49 and RMB48; therefore the bidder offering RMB50 will win the auction and buy this item at the price of RMB49.

If the quantity for one item is 2 or more at the highest price, a drawing method will be used to determine the winner.

Each group of participants takes part in one and only one auction.

The auctioneer will only announce the winner and the deal price (the second highest) at the end of each auction, but no other prices are announced. The winner pays the deal price and takes the item, while others have no any other revenue or loss.

At the end of the experiment, the experimental subjects are required to complete a corresponding questionnaire.

Once all the participants have completed the questionnaires, another group will proceed to the next session.

2.1.5 Multi-round Auction with Information exposure

Secondly, we will do the auction with information exposure. Before the auction starts, the participants will read a brief introduction to the wine grapes and wine products from different origins. Based on the same rule as in the auction without information exposure, we conduct the auction once again for one group. The information sheet is attached in the appendix.

2.2 Data

2.2.1 Dependent Variable Summary statistics

In our study, the highest bids of the three rounds for each participant on four auction items are considered as the consumer WTP for these wine products, and we have the following summary statistics for the consumer WTP for the four wine products, noted as China, US, France and Australia respectively.

The summary of the constitution of participants is given in the Table 2.3.

According to this table, our experimental design is a two-way factor design. We consider information (with/without information) and role (resident/student) as two factors that will affect the means of highest bids for all participants in the auction experiment. We take China, US, France, and Australia as four dependent variables, by conducting a two-way factor ANOVA. The results show that

1) There are no significant interaction effects between information and role for all

the four dependent variables.

2) The main effect of information is significant at 0.10 level for dependent variable Australia, which the main effects of information factor are all significant at 0.05 level for other three dependent variables.
3) There are no significant main effects of role factor for dependent variables US and France. However, the main effect of role is significant for China (at 0.05 level) and Australia (at 0.10 level).

2.2.2 Description of Variables

See Table 2.4 for the description of both response variables and predictor variables.

3. Data analysis and results

3.1 Missing Data Problem

In our data set, some of the entries of independent variables, which were collected through the ex post questionnaires, cannot be observed.

The most pressing concern regarding missing data is the extent to which the missing information influences study results. Yet because the data are missing, it is difficult to determine the impact of the data that might have been present in the study. There are two aspects of missing data that can provide us with clues regarding the extent of the influence of the missing information on study results (McKnight et al., 2007). First, the amount of missing data is related to its impact on research conclusions. Under most conditions, data sets in which large amounts of data are missing result in smaller sample sizes and potentially unrepresentative samples of the population to which we wish to generalize. Further, the available data for the remaining sample might reflect a bias, thus resulting in biased parameter estimates and misleading statistical conclusions. Second, the actual process that causes missing data can affect the validity of the inferences made from the analysis. Depending on the causal origin, missing data can have dramatic influences on the validity of study findings.

Being consistent with Little and Rubin (2002), the assumption that missingness indicators hide true values that are meaningful for analysis will be made throughout this article. When this assumption applies, it makes sense to consider analysis that effectively predict, or “impute” the unobserved values. On the other hand, if this assumption does not apply, then imputing the unobserved values makes little sense.

Before using specific techniques to do the data analysis with missing values, we have to identify the missing data pattern, which describes which values are observed in the data matrix and which values are missing, and the missing-data mechanism, which concerns the relationship between the missingness and the values of variables in the data matrix. Multiple imputation provides a useful strategy for dealing with data sets with missing values. Instead of filling in a single value for each missing value, Rubin's (1987) multiple imputation procedure replaces each missing value with a set of plausible values that represent the uncertainty about the right value to impute. These multiply imputed data sets are then analyzed by using standard procedures for complete data and combining the results from these analyses. No matter which complete-data analysis is used, the process of combining results from different imputed data sets is essentially the same. This results in statistically valid inferences that properly reflect the uncertainty due to missing values.

The SAS multiple imputation procedures assume that the missing data are missing at random (MAR), that is, the probability that an observation is missing may depend on the observed values but not the missing values. These procedures also assume that the parameters q of the data model and the parameters f of the missing data indicators are distinct. That is, knowing the values of q does not provide any additional information about f, and vice versa. If both MAR and the distinctness assumptions are satisfied, the missing data mechanism can be ignored. The MI (Multiple Imputation) procedure provides three methods for imputing missing values and the method of choice depends on the type of missing data pattern. For monotone missing data patterns, either a parametric regression method that assumes multivariate normality or a nonparametric method that uses propensity scores is appropriate. For an arbitrary missing data pattern, a Markov chain Monte Carlo (MCMC) method that assumes multivariate normality can be used.

3.2 The MCMC (Markov Chain Monte Carlo) Method

The MCMC method originated in physics as a tool for exploring equilibrium distributions of interacting molecules. In statistical applications, it is used to generate pseudo-random draws from multidimensional and otherwise intractable probability distributions via Markov chains. A Markov chain is a sequence of random variables in which the distribution of each element depends only on the value of the previous one. In MCMC simulation, one construct a Markov chain long enough for the distribution of the elements to stabilize to a stationary distribution, which is the distribution of interest. By repeatedly simulating steps of the chain, the method simulates draws from the distribution of interest. In Bayesian inference, information about unknown parameters is expressed in the form of a posterior probability distribution. MCMC has been applied as method for exploring posterior distributions in Bayesian inference. That is, through MCMC, one can simulate the entire joint posterior distribution of the unknown quantities and obtain simulation based estimates of posterior parameters that are of interest.

By applying the MCMC method procedure, the MI procedure assumes that the data are from a continuous multivariate distribution and contain missing values that can occur on any of the variables. It also assumes that the data are from a multivariate normal distribution when either the regression method or the MCMC method is used. The SAS MI and MIANALYZE procedure also assume that the missing data are missing at random (MAR), that is the probability that an observation is missing can depend on the observed values, but not on the missing values (Rubin 1976; 1987). The MAR assumption is not the same as missing completely at random (MCAR), which is a special case of MAR. Under the MCAR assumption, the missing data values are a simple random sample of all data values, and the missingness does not depend on the values of any variables in the data set.

Furthermore, the MI and MIANALYZE procedures assume that the parameters of the data model and the parameters of the model for the missing data indicators are distinct.

If both the MAR and the distinctness assumptions are satisfied, the missing-data mechanism is said to be ignorable (Rubin 1987; Schafer 1997).

3.3 Multiple Imputations and Regression Results

3.3.1 Multiple Imputations by MCMC Method

In our practice, we generate 3 imputed data sets to be used later in the regression analysis.

First of all, when applying the MCMC method, we use the EM (Expectation Maximization) estimates as a starting value with which to begin the MCMC process (Schafer 1997). Second, the missing data pattern shown in Table 3.1 lists 8 distinct missing data patterns. The table shows that the data set imputed by the MCMC method does not have a monotone missing pattern. Third, the time-series plots and autocorrelation function plots for the means of all variables included in the imputed data sets are checked to see if there is autocorrelation in the iterations (Figure 3.1-3.22). The plots show no apparent trends for all the variables.

3.3.2 Check Model Assumptions

Since we have four dependent variables (China, US, France, and Australia) in our data set, we perform four separate diagnoses for the model assumptions.

To check the normality of error terms, we apply two formal tests: Shapiro-Wilk test, and Anderson-Darling test. The results show that for the four different models all suffer a non-normality problem for the error term. Thus, we need remedial measures to overcome this problem. Here, the Box-Cox transformation of the dependent variables is introduced. The results show that $\lambda = 0.25$ is the best choice for the transformation parameter.

To test the constancy of error variances, we perform a Breusch-Pegan test for the four models. And the results show that the assumption of constancy of error variances is satisfied by all the four models.

To test the multicollinearity problem, we apply the concept of variance inflation factor (VIF). As we can see from the results, the multicollinearity is not a serious problem in our data set, since none of the VIF values is greater than 10 (Kutner, etc., 2004).

The results are shown in Table 3.2.

3.3.3 Model Selection

After performing the Box-Cox transformation on the four dependent variables, we finally come to the model used in the regression analysis:

$$Y = X\beta + \varepsilon$$

Where

Y is the observation vector of response variable with Box-Cox transformation;

X is the observation matrix of predictor variables;

β is a vector of regression coefficients;

ε is a vector of independent error terms with mean zero and equal variance.

The table shows the description for both response variables and predictor variables.

3.3.5 A Two-way ANOVA for Dependent Variables

Before we report the estimation results, we first check if the information provided and whether the participant is student or resident have influence on their preferences.

We consider with or without information exposure (information) and resident or student (role) as two factors that will affect the means of highest bids for all participants in the auction experiment. And we take China, US, France, and Australia as four dependent variables, so we have the two-way ANOVA results and discussions in Table 3.3. All tests are at level of significance 0.05.

For all the four dependent variables, no significant interaction effect between “information” and “role”, so it makes sense to report the main effects of both factors. According to ANOVA table, there is strong evidence that the means of highest bids on wine products from China, US and France are different between with-information group and without-information. And there is strong evidence that the means of highest bids on wine products from China are different between resident participants and student participants. No other significant difference is detected based on our ANOVA table.

Therefore, we can conclude that the information we provided in the experimental auction has influence on the participants' opinions on wine products.

3.3.5 Estimation Results

First, we include all the variables in the model, which is full model, in the parameter estimation, and we have the results shown in Table 3.4 for Imputation 1. Then by applying the usually used criteria: Collin Mallows C(p), AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion), we can decide which variables will be detained in the final selected models. See Table 3.5 for the estimation results for Imputation 1. Since we have similar results for Imputation 2 and 3 compared to Imputation 1, we only report results for Imputation 1.

According to the parameter estimates, we have the following concluding remarks:

1) Although our ANOVA table shows that there is a significant difference between the means of highest bids for with-information and without-information groups, our estimation results only indicate its positive effect on the participants' WTP for wine from the US.
2) Resident participants are showing higher WTP for the wine products than student participants, since residents stand a greater chance in earning more money by working full time or part time. However, students comparatively have a much lower budget constraint and expenditure per capita.
3) The household income has a positive effect on the WTP, which could be easily explained. The participants with higher household income are more likely to consume the so-called "luxury" product, wine, in China.
4) The wine products are easily accepted by younger consumers, so the age has negative effect on the WTP for wine products from China, US and France.
5) An interesting finding lies in the result that there is no significant effect of whether the participant is male or female, which implies both men and women consumers are equally likely to consume wine products and willing to pay an equivalent price. On the other hand, it also verifies the fact that wine is suitable for both men and women.

6) As for the number of family members and education level do not have significant influence on consumers' preference on wine products.
7) For the employment status, the results are a bit complicated. For participants who have full time jobs are likely to pay less for wine products from China and US. As for those who have part time jobs, they are willing to pay less for American wine and pay more for French and Australian wines. A situation of unemployment would have negative effect on the willingness-to-pay for Chinese wine.

4. Conclusion

In this article, we apply the second price sealed auction mechanism to study the Chinese consumers' WTP for four wine products, which are from China, the US, France, and Australia. One of our goals is to tell the difference of consumers' preferences between the "old world" wines (French) and "new world" wines (Chinese, American, and Australian). Our data shows that Chinese consumers in Beijing and Shanghai are willing to pay more for the "old world" wines from France than the "new world" wines from China, American, and Australia, which indicates their greater sense of identity on the French wines. It is so common in Beijing and Shanghai that French wines dominate the shelf space for foreign wine products. However, the local Chinese wines also account for a considerable market share because of the price superiority, which also results in the lowest WTP for Chinese wines in our auction.

To deal with the missing data problem in the data set, we use the MCMC (Markov Chain Monte Carlo) method. The resident participants show higher WTP than college students for all the four wine products in the auctions. Another interesting finding is that the participants in the group with information exposure are offering higher bids for the wine products. As for the factors that affect the participants' WTP, younger, male, employed, well educated participants are willing to pay more for wine products. Furthermore, household income and number of household members are positively affecting the WTP of participants for the wine products.

Our results provide meaningful and insightful marketing suggestions for the “new world” and Chinese wine producers, such as the target consumers and pricing strategy. First of all, the consumers’ sense of identity is important for the new world wine producers. Even though the new world wines are of good quality, consumers will not buy them if they do not know about the wine. So the information exposure, or in other word, communication will play an important role in the wine marketing. This can be done in a lot of ways, such as industrial expos, advertising, and promotion. Second, different wine products must cater to different needs of consumers, so the producers should convey different information on different wine products. Third, pricing strategy is another key factor that should be taken into account. The producers not only consider their production cost, but also consider the Chinese local market. We notice that the mean WTP for the four wine products are all lower than the real market prices, which implies that the Chinese wine market is still in its early days. In consequence, high-end products with high prices might not be a good idea for the “new world” wines.

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Appendix: Tables and Figures

Table 2.1

The Wine Products for Auction

Origin of Production	Brand Name	Year of Production
China	Dragon Seal	2005
USA	Chateau Saint Pierre	2005
France		
Australia	Lindemans Cawarra	2005

Table 2.2

The Constitution of Participants

Counts	**With information**	**Without information**
Residents	96	99
Students	110	118

Table 2.3

The Summary Statistics for Response Variables

Variable	Mean	Standard deviation	Median	Range	Highest	Lowest
China	21.42	27.97	16	217	218	1
US	23.45	28.66	15	199	200	1
France	33.64	51.72	20	417	418	1
Australia	27.75	38.54	19	268	269	1

Table 2.4

The Description of Response Variables and Predictor Variables

Response Variable	
China	The highest bid in the three rounds of each participant on the wine product from China^0.25
US	The highest bid in the three rounds of each participant on the wine product from the US^0.25
France	The highest bid in the three rounds of each participant on the wine product from France^0.25
Australia	The highest bid in the three rounds of each participant on the wine product from Australia^0.25
Predictor Variable	
information	1=with information, 0=without information
role	1=resident, 0=student
gender	1=male, 0=female
age	Age of the participant
income	Monthly household income/1000
member	The number of family members in the household
education	Level of education (0=elementary school or below, 1=high school, 2=junior college, 3=undergraduate, 4=graduate)
fulltime	1=full time, 0=otherwise
partime	1=part time, 0=otherwise
unemployed	1=unemployed, 0=otherwise
retired	1=retired, 0=otherwise

Table 3.1

Missing Data Patterns

Missing Data Patterns															
Group	ch	us	fr	au	info	role	gender	logage	logincome	member	edu	fulltime	partime	unemployed	retired
1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
2	X	X	X	X	X	X	X	X	X	X	.	X	X	X	X
3	X	X	X	X	X	X	X	X	X	.	X	X	X	X	X
4	X	X	X	X	X	X	X	X	.	X	X	X	X	X	X
5	X	X	X	X	X	X	X	X	.	X	.	X	X	X	X
6	X	X	X	X	X	X	X	X	.	.	X	X	X	X	X
7	X	X	X	X	X	X	X	X	.	.	.	X	X	X	X
8	X	X	X	X	X	X	X	.	X	X	X	X	X	X	X

Missing Data Patterns											
			Group Means								
Group	Freq	Percent	ch	us	fr	au	info	role	gender	logage	logincome
1	321	75.89	20.753894	21.990654	30.735202	24.149533	0.252336	0.520249	0.436137	1.483385	3.442058
2	1	0.24	1.000000	1.000000	30.000000	1.000000	0	1.000000	0	1.763428	3.204120
3	2	0.47	25.500000	32.000000	34.000000	31.500000	1.000000	1.000000	0	1.814858	3.088046
4	77	18.20	16.636364	19.649351	24.935065	22.090909	0.142857	0.194805	0.597403	1.428079	.
5	2	0.47	7.000000	5.500000	13.500000	6.000000	0.500000	1.000000	1.000000	1.628359	.
6	14	3.31	18.785714	20.642857	28.571429	23.928571	0	0.285714	0.571429	1.488953	.
7	2	0.47	24.000000	29.000000	39.000000	34.000000	0	1.000000	0.500000	1.778151	.
8	4	0.95	5.500000	5.750000	25.250000	21.000000	0.250000	0.500000	0.250000	.	3.486367

Table 3.1 Continued

Missing Data Patterns						
	Group Means					
Group	member	edu	fulltime	partime	unemployed	retired
1	3.448598	2.261682	0.208723	0.074766	0.040498	0.199377
2	3.000000	.	0	0	0	1.000000
3	.	0.500000	0	0	0.500000	0.500000
4	3.532468	2.558442	0.025974	0.025974	0.064935	0.077922
5	4.000000	.	0.500000	0	0.500000	0
6	.	2.428571	0	0	0.071429	0.214286
7	.	.	0	0	0	1.000000
8	4.000000	2.000000	0	0	0	0.500000

Table 3.2

Check for Model Assumption in Imputed Data Sets

	Test for Normality		**Test for Constancy of Variance**
Response Variable	Shapiro-Wilk	Anderson-Darling	Breusch-Pagan*
China	Pr<0.0001	Pr<0.005	0.4950, 0.5140, 0.5323
US	Pr<0.0001	Pr<0.005	0.3335, 0.7084, 0.5571
France	Pr<0.0001	Pr<0.005	0.6414, 0.7416, 0.7242
Australia	Pr<0.0001	Pr<0.005	0.4472, 0.7524, 0.6101

*For the Breusch-Pagan tests, the three numbers are corresponding to the 3 imputation data sets respectively.

Table 3.3 Two-way ANOVA Table for Factors: "Information" and "Role"

Dependent Variables	Source	DF	Type III SS	Mean Square	F values	Pr > F
China	Information	1	3883.9170	3883.9170	5.14	0.0239
	Role	1	6750.4897	6750.4897	8.93	0.0030
	Information*Role	1	2667.7267	2667.7267	3.53	0.0609
US	Information	1	6670.5405	6670.5405	8.30	0.0042
	Role	1	1978.4758	1978.4758	2.46	0.1174
	Information*Role	1	929.5479	929.5479	1.16	0.2828
France	Information	1	16756.0713	16756.0713	6.39	0.0118
	Role	1	6846.9547	6846.9547	2.61	0.1068
	Information*Role	1	5846.2096	5846.2096	2.23	0.1361
Australia	Information	1	4311.0783	4311.0783	2.93	0.0874
	Role	1	5635.8912	5635.8912	3.84	0.0508
	Information*Role	1	1165.3236	1165.3236	0.79	0.3736

Table 3.4

Parameter Estimates (Full Model)

Imputation: 1

Parameter	China	US	France	Australia
Intercept	1.73268*	1.75949*	1.93945*	1.56991*
Info	0.06854	0.14924***	0.11315	0.09453
Role	0.34744**	0.42435**	0.47820*	0.37551**
Gender	0.07628	-0.00118	0.03381	0.00870
Age	-0.00998**	-0.00882**	-0.01045**	-0.00530
Income	0.03879*	0.03666*	0.03696*	0.04713*
Member	0.03074	-0.00090394	0.00617	0.00791
Edu	0.03739	0.06532	0.04814	0.0441**
Fulltime	-0.20277	-0.24205***	-0.19053	-0.14167
Partime	0.01916	0.05732	0.11424	0.16377
Unemployed	-0.32131**	-0.22489	-0.12403	-0.15136

*Significant at 0.01

** Significant at 0.05

***Significant at 0.10

Table 3.5

Parameter Estimates (Model Selection by C(p), AIC, BIC Criteria)

Imputation 1

	China	**US**	**France**	**Australia**
Intercept	2.00106*	1.77207*	2.10640*	1.42697
Info	-	0.15072***	-	
Role	0.36645*	0.46549*	0.32497*	0.23710*
Gender	0.08223	-	-	-
Age	-0.01200*	-0.00964*	-0.00935*	-
Income	0.03871*	0.03682*	0.03513*	0.04745*
Member	-	-	-	-
Edu	-	0.06574	-	-
Fulltime	-0.21374**	-0.27379*	-	-
Partime	-	-0.24788***	0.25982**	0.30266*
Unemployed	-0.33834**	-	-	-

*Significant at 0.01

**Significant at 0.05

***Significant at 0.10