Consumer Preferences for Quality and Safety Attributes of Duck in Restaurant Entrees:
Is China A Viable Market for The U.S. Duck Industry?

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Introduction

Consumers' food preferences and purchasing behavior in China are rapidly evolving as a result of robust economic growth, rapid global integration, and food safety failures in the domestic food production and marketing system. The food environment in China is characterized by growing demand for variety and quality on the one hand (Gale and Huang 2007, Popkin 1999) and uncertainty and concern for food safety on the other (Ortega et al. 2012). Many urban consumers in China are willing to pay premiums for safe, high quality food in retail markets (Liu, Zuzanna and Verbeke 2013). Consumers' preferences for search (color, fat content, etc.), experience (taste, tenderness, etc.) and credence (brand, traceability, various labeling schemes, etc.) attributes of various meat products have been widely examined, particularly in the United States and Europe. There are several studies that focus on meat preferences in China's retail sector, such as Ortega et al. (2009).

All of these studies focus on the food retail sector and neglect the food service sector. As the income share of food-away-from-home increases, consumers' preferences for prepared food in the food service sector, as opposed to just groceries from the food retail sector, deserve additional attention. In 2010, the food service industry in China consisted of nearly 6 million outlets and generated over 330 billion dollars (Agriculture and Agri-Food Canada 2012). Although, hospitality management and tourism literature investigates food service sector, it emphasizes consumer dining experience preferences, focusing on services other than food ingredient quality (Ali and Nath 2013).

We use duck consumption in the food service sector in China as a case in this empirical study. China is the largest producer and consumer of duck in the world, with 2.7 million tonnes (over $4.5 billion) produced, 42.6 thousand tonnes ($92 million) exported, and 55.8 thousand tonnes ($109 million) imported in 2011. Unprecedented economic growth and the maturation of the Chinese market in recent decades have created demand for high-quality duck, an enticing new marketing opportunity for American duck producers. Firms in the EU have already begun marketing their duck breed in the Chinese market. However, although American duck producers are well positioned to supply high-quality duck products to the food service industry, little is known about the size, demographics, and preferences of Chinese duck consumers.

This study is innovative in three manners. First, it explores consumer attribute preferences and choice behavior for poultry meat used in restaurant entrees. Second, it highlights the market for duck in China, a huge market currently neglected in literature. Finally, it examines the impact of regional and cultural diversity in China on consumer preferences and willingness to pay for restaurant entrée attributes.

Survey

A unique dataset was collected during the summer of 2013 in Beijing, Shanghai, Chengdu, and Guangzhou, which represent four geographic and cultural regions of urban China. Consumers in restaurants serving duck dishes were randomly selected. Restaurants ranged from large luxury restaurants with many private dining rooms to small mom-and-pop restaurants with scarcely ten tables. Trained enumerators conducted face-to-face interviews of the consumers as they dined in the restaurants in order to mimic real purchasing and choice environments. Each survey elicited demographic information, dining out and duck consumption behavior, and nine choice scenarios. A total of 505 valid individual surveys with 4,526 choice situations were obtained. Consumers demographic characteristics are summarized in Table 1 and dining out and duck purchasing behavior characteristics are provided in Table 2.

Choice Experiment

A choice experiment presents consumers with two or more options described by a bundle of attributes or the option to purchase nothing. Choice experiment methodology stems from the Lancastrian approach to consumer theory which states consumers do not derive value from the good itself, but instead extract value from the attributes a good possesses. In addition, goods may possess many attributes, these attributes may be shared by many goods, and a collection of goods may possess different attributes than each good separately (Lancaster 1966). A consumer chooses the option that maximizes his or her utility. In the current study, restaurant consumers maximize their utility by selecting the duck entrée with the attributes they desire or by choosing to purchase nothing.

Several practical benefits of choice experiments include their similarity to real purchasing decisions, their conformance to random utility theory, and their consistency with revealed preference methods (Adamowicz, et al. 1998, Carlsson and Martinsson 2001, Lusk and Schroeder 2004, Carlsson, Frykblom and Lagerkvist 2007, Ortega, et al. 2011). In this study, restaurant consumers considered nine separate scenarios each with two product options described by price, food safety, quality, brand, and biotechnology attributes, or the option not to purchase. Information regarding the meaning of these five attributes was provided before beginning the choice experiment exercise (definitions are provided in Table 3). After reviewing the attributes' descriptions, consumers were instructed to make selections as if actually facing these product choices and making real purchasing decisions. A sample choice experiment scenario is provided in Table 4.

Random Utility Theory

Like in choice experiments, random utility theory hinges on the assumption that consumers will maximize their expected utility, subject to available choice options. Following Ortega et al. (2012), consumer n's latent utility, U_{nit}, from selecting an alternative, i, from choice set C with J alternatives in situation t is random because only some information is observable to the researcher. Therefore utility is comprised of an observable (deterministic) component, V_{nit}, and an unobservable (random) component, ε_{nit} written as:

(1) $$U_{nit} = V_{nit} + \varepsilon_{nit} \,.$$

Consumer n will chooses alternative i if the utility from selecting alternative i outweighs the expected utility of any other option. The probability that consumer n chooses alternative i in situation t is specified as:

(2) $$P_{nit} = Prob\left(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt}\right) \;\; (\forall j \in C \; and \; \forall j \neq i)$$

Based on the assumption that ε_{nit} is independent and identically distributed over all alternatives and situations, the multinomial logit (MNL) form is given by:

(3) $$P_{nit} = \frac{e^{V_{nit}}}{\sum_j e^{V_{njt}}}$$

When using the MNL form, consumers are assumed to have identical tastes and preferences, which is often unrealistic. Recent studies advocate using more flexible models that allow consumers' preferences to be heterogeneous (Alfnes 2004, Tonsor, Olynk and Wolf 2009). Two models used to accommodate preference heterogeneity are the random parameters logit (RPL) model and the latent class model (LCM). Some recent examples combining choice experiment methodology with RPL or LCM are Tonsor et al. (2009) and Ortega et al. (2011).

Random Parameters Logit

RPL models allow consumers' preferences for each product attribute to be heterogeneous. The deterministic component of utility, $\mathrm{V_{nit}}$, is assumed to be linear in parameters and takes the form:

$$V_{nit} = \beta' x_{nit} \tag{4}$$

where β' is a vector of random parameters, each with its own mean and variance, thus representing each individuals' preferences over alternatives. Its distribution is described by the probability density function $\mathrm{f}(.)$ such that if the parameters are non-random (e.g. they are fixed at β_c) the distribution collapses. That is to say $\mathrm{f}(\beta_c) \to \infty$ and $\mathrm{f}(\beta) = 0$ otherwise (D. Ortega, H. Wang, et al. 2012). The observable characteristics of alternative i in situation t are expressed as the vector, x_{nit}. Following Train (2003), the expected probability that individual *n* selects alternative *i* from choice set *C* in situation t is given by:

$$\mathrm{EP_{nit}} = \int \mathrm{P_{nit}}\, \mathrm{f}(\beta)\mathrm{d}\beta = \int \frac{e^{V_{nit}}}{\sum_j e^{V_{njt}}} \mathrm{f}(\beta)\mathrm{d}\beta \tag{5}$$

In the current study, we are interested in the marginal contributions of price (Price_{nit}), whether product brand information is provided (Brand_{nit}), the quality level expressed on the menu ($\mathrm{Quality}_{nit}$), whether the product carries additional food safety assurance ($\mathrm{Certified}_{nit}$), the biotechnological origin (US_{nit} or EU_{nit}, with China as the base), and the choice to purchase neither alternative (OptOut_{nit}). With the exception of price, all explanatory variables are dummy variables and are random and normally distributed (price is fixed) (D. Ortega, H. Wang, et al. 2012, Ubilava and Foster 2009). The observable portion of utility, V_{nit}, in our base RPL model takes the form:

(6) $$\mathrm{V}_{nit} = \beta_p \mathrm{Price}_{nit} + \beta_1 \mathrm{Brand}_{nit} + \beta_2 \mathrm{Quality}_{nit} + \beta_3 \mathrm{Certified}_{nit} + \beta_4 \mathrm{US}_{nit} + \beta_5 \mathrm{EU}_{nit} + \beta_6 \mathrm{OptOut}_{nit}$$

Latent Class Model

A latent class model is used to describe consumer preferences that can be categorized into groups forming consumer classes. Consumers' tastes and preferences are allowed to be different across classes but homogenous within classes (D. L. Ortega, et al. 2011). In a LCM, N consumers are sorted into S latent classes (Boxall and Adamowicz 2002). The distribution of the probability parameter is discrete and takes S different values (Train 2003). Following Ortega et al. (2012) the expected probability that consumer n chooses alternative i in situation t is defined as:

(7) $$EP_{nit} = \sum_{s=1}^{S} P_{nit}^{s} R_{ns} = \sum_{s=1}^{S} \frac{e^{(\beta_s' x_{nit})}}{\sum_j e^{(\beta_s' x_{njt})}} R_{ns}$$

where β_s' are the class specific parameters for class s and R_{ns} is the probability that consumer n belongs to class s (Ouma, Abdulai and Drucker 2007) and can be expressed as:

$$(8) \qquad R_{ns} = \frac{e^{(\theta_s' Z_n)}}{\sum_r e^{(\theta_s' Z_n)}}$$

where Z_n is observable characteristics of a consumer that affect class membership and θ_s' is a vector of class-specific parameters.

Willingness to Pay

The coefficients estimated by the LCM and RPL models have no directly interpretable meaning because of the non-cardinal nature of utility. Therefore, estimated coefficients are converted to willingness to pay (WTP) measures which are defined as:

$$(9) \qquad WTP_k = -2\ \frac{MU_k}{MU_p} = -2\ \frac{\beta_k}{\beta_p}$$

where β_k is the estimated parameter of the k^{th} attribute (k = 1,…5) and β_p is the estimated price coefficient from equation (6). Specifically, β_k is the partial derivative of indirect utility with respect to the k^{th} attribute when other attributes are absent and using the variables' sample means. Furthermore, β_p may be thought of as an income penalty such that the negative marginal utility of price is an acceptable proxy for marginal utility of income (Olynk and Ortega 2012). All attribute WTPs are multiplied by 2 to counteract the effect of effects coding with the exception of OptOut[3] (Lusk 2003, D. L. Ortega, et al. 2011).

[3] An effects coded variable takes the value 1 if present, -1 if absent, and 0 if the consumer elects to purchase neither option.

We use the mean β coefficient estimates to calculate the mean WTP by using Equation (9). In order to test the significance of the WTP estimates, we need to know the variance of the WTP estimates. Hole (2007) finds the delta method, the Fieller method, and the Krinsky-Rob boostrapping technique all provide comparable estimates of WTP variance. In our base RPL and LCM models we use the delta method (Greene 2003, Hole 2007) which is calculated for each k by

$$(10) \qquad var\left(\widehat{WTP}_k\right) = \left[\left(\widehat{WTP}_{\beta_k}\right)^2 var\left(\hat{\beta}_k\right) + \left(\widehat{WTP}_{\beta_p}\right)^2 var\left(\hat{\beta}_p\right) + 2\widehat{WTP}_{\beta_k}\widehat{WTP}_{\beta_p} covar\left(\hat{\beta}_k, \hat{\beta}_p\right)\right]$$

$$= \left[\left(\frac{-2}{\hat{\beta}_p}\right)^2 var\left(\hat{\beta}_k\right) + \left(\frac{2\hat{\beta}_k}{\hat{\beta}_p^2}\right)^2 var\left(\hat{\beta}_p\right) + 2\left(\frac{-2}{\hat{\beta}_p}\right)\left(\frac{2\hat{\beta}_k}{\hat{\beta}_p^2}\right) covar\left(\hat{\beta}_k, \hat{\beta}_p\right)\right].$$

where $WTP_{\beta_l} = \partial WTP_l / \partial \beta_l \ (l = k \ and \ p)$. Assuming WTP is approximately normally distributed, the lower and upper bounds of its 95 percent confidence interval can be calculated as:

$$(11) \qquad \widehat{WTP}_k \mp 1.96\sqrt{var(\widehat{WTP}_k)}$$

So long as the WTP confidence intervals do not contain zero, the estimates can be viewed with a good measure of assurance.

Additional Methods

In order to explore potential variation in willingness to pay estimates across regions, demographic segments, and groups with similar purchasing behaviors and attribute preferences, we adopt two alternative estimation techniques. First, we allow regional, demographic, behavior, and attribute variables to enter the RPL model via interaction terms. Second, we run regressions with individual-specific WTP estimations as the dependent variable and regional, demographic, and behavioral characteristics as the explanatory variables.

Allowing variable crosses to enter the model is executed in two manners. First, crosses between consumer characteristics and product attributes are generated as a simple multiplication between either a continuous characteristic (age) or a dummy variable (high income). In either case, the resulting new variable may be placed directly into the RPL model, remembering to avoid perfect multicollinearity problems associated with the inclusion of all dummies in a set. The second method exploits the two-way effects built into the choice experiment design which allows interactions between product attributes to enter the RPL model (Olynk and Ortega 2012). The non-effects coded attributes multiplied and then effects coded.

Calculating the variance of WTP in models that include interaction terms necessitates abandoning the delta method which assumes that WTP is symmetrically distributed. Instead, we use a parametric bootstrapping method proposed by Krinsky-Robb (1986) that relaxes the assumption that WTP is symmetrically distributed. A distribution of 1000 observations for each WTP estimate was simulated using Halton draws from a multivariate normal distribution which is parameterized with the coefficients and variance terms estimated by the model (Olynk and Ortega 2012, D. Ortega, H. H. Wang, et al. 2011). The upper and lower bounds of the 95 percent confidence interval are then the 26th and 975th sorted estimates of WTP (Hole 2007).

Finally, as an alternative to including variable crosses in the model, we use standard OLS regressions to explore possible relationships between WTP for attributes and consumer characteristics. More specifically, we use individual's estimated coefficients produced by NLOGIT to calculate individuals' WTP for each attribute. We then use individuals' WTP as the dependent variable and a wide range of demographic and behavior characteristics as explanatory variables.

Results and Discussion

All RPL model coefficients and standard deviations are significant at the 1 percent level, indicating that consumer preferences for each of the five attributes and the option not to purchase are heterogeneous. All LCM model coefficients are also significant at the 1 percent level, with the exception of EU biotechnology in class 1, and point toward a two segment consumer base. The RPL and LCM model coefficients, standard deviations, standard errors, and class membership probabilities can be found in Table 5.

As stated earlier, the coefficients themselves are not useful and instead we use WTP calculations to compare consumer preferences over each attribute. According to the RPL model, consumers are willing to pay premiums for branded (¥69), premium quality (¥61), and safety certified (¥100) duck entrees, while discounting US (-¥36) and EU (-¥22) biotechnology in duck entrees. As a rule of thumb, if the 95 percent confidence intervals of the mean WTPs do not overlap, they are considered significantly different from one another. From Table 6, we see that WTP for certified is higher than WTP for quality, WTP for quality and brand are similar, WTP for imported biotechnology is similar for the US and EU, and OptOut is by far the lowest.

The LCM classes are termed "Duck Connoisseurs" and "Budget Diners" based on the relative magnitudes of the WTP values. Both groups are willing to pay premiums or discount the same attributes, but to different degrees. Each class contains about half of the sample population, which aligns with the statistic that only about half of the sample population reports ordering duck fairly often while dining out.

Regional Variation

We constructed an RPL model that could account for potential differences in preferences across the four survey cities. We introduce attribute-city interaction terms into the basic model found in Equation (6), leaving Beijing as our base, such that:

$$(12) \qquad V_{nit} = \beta_p Price_{nit} + \beta_1 Brand_{nit} + \beta_2 Quality_{nit} + \beta_3 Certified_{nit} + \beta_4 US_{nit} + \beta_5 EU_{nit} + \beta_6 Brand \cdot S_{nit} + \beta_7 Brand \cdot C_{nit} + \beta_8 Brand \cdot G_{nit} + \beta_9 Quality \cdot S_{nit} + \beta_{10} Quality \cdot C_{nit} + \beta_{11} Quality \cdot G_{nit} + \beta_{12} Certified \cdot S_{nit} + \beta_{13} Certified \cdot C_{nit} + \beta_{14} Certified \cdot G_{nit} + \beta_{15} US \cdot S_{nit} + \beta_{16} US \cdot C_{nit} + \beta_{17} US \cdot G_{nit} + \beta_{18} EU \cdot S_{nit} + \beta_{19} EU \cdot C_{nit} + \beta_{20} EU \cdot G_{nit} + \beta_{21}\, OptOut_{nit}$$

where S, C, and G stand for Shanghai, Chengdu, and Guangzhou. All estimated coefficients for Beijing (the base) are significant at the one percent level, as are the standard deviations, indicating heterogeneity is indeed present. The model coefficients, standard deviations, and standard errors are presented in Table 7 and the willingness to pay values and their 95 percent confidence intervals are presented in Table 8

	Base: Beijing[1,2,3]	Shanghai	Chengdu	Guangzhou
Brand	0.384 (0.083)***	0.151 (0.109)	0.061 (0.118)	0.266 (0.112)**
Quality	0.298 (0.073)***	0.216 (0.097)**	0.050 (0.100)	0.327 (0.099)***
Certified	0.736 (0.096)***	-0.022 (0.124)	0.202 (0.134)	-0.109 (0.125)
US	−0.567 (0.107)***	0.322 (0.131)***	0.336 (0.146)**	0.514 (0.139)***
EU	−0.401 (0.105)***	0.293 (0.129)**	0.073 (0.145)	0.542 (0.137)***
OptOut	−2.249 (0.163)***			
Price	−0.015 (0.001)***			

S.D.(Brand)	0.558 (0.049)***
S.D.(Quality)	0.442 (0.058)***
S.D.(Certified)	0.599 (0.078)***
S.D.(US)	0.933 (0.059)***
S.D.(EU)	0.780 (0.062)***
S.D.(OptOut)	2.269 (0.131)***

[1] Standard errors shown in parenthesis ().
[2] Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 8.

Consumers are willing to pay most for certified duck entrees on average, followed by brand and quality, while consumers discounted EU and US biotechnology duck entrees. In Shanghai and Guangzhou, consumers do not discount EU biotech as deeply as Beijing or Chengdu, and Guangzhou consumers appear to be WTP a premium for EU imported biotechnology. Chengdu consumers are WTP a great deal more for certified entrees than consumers in the other cities, on average, and discount EU and US biotechnology steeply. A cursory view of the differences in WTP for brand and quality may lead to the conclusion that consumers in different cities value these attributes relatively differently, however, the confidence intervals overlap indicating they are not necessarily different from one another.

Results are all reasonable given the immense popularity of Peking (or Beijing) roast duck in Beijing, the fact that Hong Kong (a city not far from Guangzhou) is the largest importer of duck meat in the world, the epicurean culture in Shanghai, and the relative economic paucity of Chengdu. Interestingly, Guangzhou and Shanghai consumers are much less averse to imported products, particularly EU biotechnology. This likely reflects commercial and global integration common to these cities that has allowed foreign products to penetrate these markets. Guangzhou also is a close neighbor to the duck importing giant, Hong Kong. Beijing and Chengdu consumers strongly prefer domestic duck likely because of the traditional regional cuisine that calls for strong-tasting, domestic ducks.

Demographic and Behavior impacts

In addition to regional differences in consumer preferences we hypothesize there are significant differences across demographic groups and groups with similar purchasing behavior. To test this hypothesis we create to RPL models, one with attribute-demographic interaction terms and one with attribute behavior interaction terms. The model results and WTP are shown in Table 9 and Table 10.

Although the WTP estimates do vary somewhat, in general the confidence intervals overlap, indicating that they are not statistically different from one another. A few exceptions include high income consumers' WTP for US and EU biotechnology in duck entrees. These consumers are willing to more, on average, than consumers from other income categories. One explanation for this is that high income consumers are often early adopters and more open to new products and able and willing to pay for them. When considering groups of consumers with different behavior characteristics, we see that consumer who eat alone or only with one other person exhibit significantly lower willingness to pay for brand. One explanation is that consumers are more WTP for quality or safety when in a social setting, whether because of peer pressure or for celebration.

Attribute Preference Interactions

We also explore consumer preference and WTP heterogeneity when two attributes are present in combination. We interact biotech country of origin with brand, quality, and certification to determine which combinations extract premiums and which are discounted. All duck entrees in the choice experiment were presented to consumers with a biotechnological country of origin, either from the US, the EU, or China. Therefore Equation (6) is modified to include interaction terms such that:

$$(13)\quad V_{nit} = \beta_p Price_{nit} + \beta_1 Brand \cdot US_{nit} + \beta_2 Brand \cdot EU_{nit} + \beta_3 Brand \cdot China_{nit} + \beta_4 Quality \cdot US_{nit} + \beta_5 Quality \cdot EU_{nit} + \beta_6 Quality \cdot China_{nit} + \beta_7 Certified \cdot US_{nit} + \beta_8 Certified \cdot EU_{nit} + \beta_9 Certified \cdot China + \beta_{10}\, OptOut_{nit}$$

All model results and WTP estimates are presented in Table 11. Results indicate that consumers, on average, are willing to pay premiums for all branded, quality, and certified products, regardless of origin. This is interesting, given that most consumers discount imported biotechnology when not combined with other quality or safety guarantees. China is still the favored biotech country, followed by the EU and US. Interestingly, these results suggest that China’s food service industry may be a viable market for foreign biotechnology so long as products also carry other quality and safety guarantees.

Alternative Estimation Techniques

To explore another avenue to dicuss the potential impacts of region, demographics, and behavior on preferences and willingness to pay for duck entrée attributes, we use individual-specific WTP estimates in simple OLS regressions as:

$$(14) \qquad WTP_{nk} = \beta_0 + \beta_1 Shanghai_n + \beta_2 Chengdu_n + \beta_3 Guangzhou_n + \beta_4 GroupA_n + \beta_5 GroupS_n + \beta_6 GroupR_n + \beta_7 AvgPrice_n + \beta_8 HighInc_n + \beta_9 ChangeInc_n + \beta_{10} Migrant_n + \varepsilon_n$$

where n designates individual specific characteristics and k refers attributes (brand, quality, etc.). The results of the 5 regressions are presented in Table 12. Although models could have a better fit the variables are all jointly significant in explaining WTP.

Results align nicely with the each of the RPL models' results. For example, the regressions indicate that being from Shanghai and Guangzhou positively contributes to WTP for imported biotechnology. Being from a high income group increased WTP for imported biotechnology. Also, dining in groups larger than two more often positively contributes to WTP for branded and certified duck entrees. Finally, migrants tend to be less willing to pay for imported biotech and brand.

Conclusions

Consumers' preferences and willingness to pay for quality attributes of meat and poultry can be different in grocery stores versus in cooked dishes in restaurants. Our empirical results indicate that on average, Chinese consumers currently discount imported duck biotechnology, primarily due to taste, while proffering premiums for branded, premium quality, and certified ducks. We also see a divide in the relative sizes of WTP amongst consumers who often consume duck in restaurants and those who do not. Additionally, city represents a distinct market where consumers value product attributes differently. These results are justified given the differences in economic development, in traditional, regional, and cultural cuisines, as well as in the current development status of the food marketing system in China. Although consumers initially appear quite averse to imported duck biotechnology, our results reveal certain groups value food safety and quality attributes very much and may also favor imported biotechnology. For example, consumers in Shanghai and Guangzhou and high income consumers are either do not heavily discount or are WTP pay premiums for imported biotechnology. Finally, most consumers are willing to pay premiums when brand, quality, and certified appear in concert with imported biotechnology, indicating that China may indeed be a viable market for American duck.

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Appendix: Tables

Table 1: Consumer Demographic Summary Statistics

Variable	Description	Total	Beijing	Shanghai	Chengdu	Guangzhou
Gender	Male	52%	54%	49%	54%	52%
	Female	48%	46%	51%	47%	48%
Age	As of Summer 2013[1]	34 (12)	32 (10)	33 (14)	36 (13)	35 (10)
Education	High school degree	19%	11%	18%	37%	10%
	Associates/technical/trade degree	18%	16%	26%	11%	16%
	Bachelors' degree	36%	44%	39%	27%	35%
	Graduate degree	26%	29%	16%	23%	35%
	Other	1%	0%	1%	2%	0%
Household Size	Adults	2.9	2.7	2.8	3.0	3.1
	Children	0.5	0.5	0.4	0.6	0.7
	Total members	3.4	3.1	3.2	3.6	3.8
Household Income (2013)	<50,000 RMB	24%	20%	24%	41%	11%
	50,000 - 70,000 RMB	19%	20%	14%	21%	22%
	70,00 - 100,000 RMB	15%	14%	12%	18%	18%
	100,000 - 150,000 RMB	18%	18%	24%	9%	20%
	> 150,000 RMB	22%	24%	25%	9%	29%
Income Change	Income increased in past 2 years	35%	33%	40%	35%	30%
	Income decreased in past 2 years	10%	10%	9%	9%	10%
	Income constant in past 2 years	55%	54%	51%	54%	58%
Migration	Migrated into the city in past 2 years	25%	27%	19%	33%	22%
	Not migrated in past 2 years	75%	73%	81%	68%	78%

[1] Standard deviations appear in parenthesis ()

Table 2: Consumer Dining Out and Duck Purchasing Behavior Summary Statistics

Variable	Description	Total	Beijing	Shanghai	Chengdu	Guangzhou
Dining Out	Average Times/Month[1]	8 (9)	12 (15)	7 (7)	6 (7)	[illegible]
Dine in Group (>2)	Almost always	70%	70%	72%	71%	67%
	Sometimes	25%	25%	24%	24%	26%
	Rarely	5%	4%	4%	6%	6%
	Never	0%	0%	1%	0%	1%
Frequency Ordering Duck	Almost always	7%	4%	7%	6%	11%
	Sometimes	43%	46%	49%	35%	41%
	Rarely	43%	47%	35%	50%	42%
	Never	7%	3%	9%	9%	6%
Duck Cut Ordered Most Frequently	Whole or half duck	53.9	65.5	57.0	43.3	50.4
	Major cuts (e.g. breast, etc.)	21.8	11.2	21.1	25.2	28.8
	Minor cuts (e.g. feet, etc.)	22.7	19.0	21.1	29.9	20.8
Entrée Price	Average RMB for meat entrée[1]	47 (29)	58 (41)	51 (26)	32 (18)	46 (22)

[1] Standard deviations appear in parenthesis ()

Comment [WHH1]: Explain.

Table 3: Duck Product Attribute Descriptions for Choice Experiment

Attributes	Pre-Choice Attribute Descriptions	Options
Price	Price for one whole duck dish (excluding side dishes)	40, 60, 80, 100 ¥/each
Food Safety	With or without food safety measures beyond minimum government regulations such as “No harm to public”, “Green food”, “Organic” certifications	Certified/No claim
Quality	Item labeled as “premium duck” or no labeling on the menu	Premium/Regular
Brand	Duck brand information is or is not provided	Branded/No Brand
Biotechnology	Breed or other technology associated with the duck’s production is from a particular country	US/EU/China

Table 4: Sample Choice Experiment Scenario

Duck Characteristics	Option A	Option B	Option C
Whole Duck Price (Yuan)	40	60	Purchase Neither
Food Safety	Certified	Certified	
Quality	Regular	Premium	
Brand	No Brand	No Brand	
Biotechnology	Europe	United States	
I choose:			

Table 5: RPL and LCM Model Results

	Random Parameters[1,2,3]			Latent Class					
Variable				Class 1: "Duck Connoisseurs"			Class 2: "Budget Diners"		
Brand	0.509	(0.041)	***	0.245	(0.037)	***	0.465	(0.050)	***
Quality	0.449	(0.037)	***	0.316	(0.033)	***	0.305	(0.044)	***
Certified	0.741	(0.044)	***	0.412	(0.040)	***	0.621	(0.048)	***
US	−0.268	(0.051)	***	−0.099	(0.038)	***	−0.388	(0.057)	***
EU	−0.162	(0.050)	***	−0.061	(0.042)	***	−0.263	(0.063)	***
OptOut	−2.256	(0.159)	***	−2.632	(0.220)	***	−0.909	(0.158)	***
Price	−0.015	(0.001)	***	−0.005	(0.001)	***	−0.020	(0.002)	***
S.D.(Brand)	0.576	(0.049)	***						
S.D.(Quality)	0.456	(0.060)	***						
S.D.(Certified)	0.579	(0.087)	***						
S.D.(US)	0.921	(0.057)	***						
S.D.(EU)	0.774	(0.065)	***						
S.D.(OptOut)	2.277	(0.131)	***						
Class Prob.		NA			55%			45%	

[1]Standard errors shown in parenthesis ().
[2]Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 6: RPL and LCM Willingness to Pay Estimates

	Random Parameters Model[1,2,3]		Latent Class Model			
Variable			Class 1: "Duck Connoisseurs"		Class 2: "Budget Diners"	
Brand	68.77 [54, 83]	***	107.09 [31, 183]	***	45.99 [34, 58]	***
Quality	60.58 [47, 75]	***	138.02 [43, 233]	***	30.17 [19, 42]	***
Certified	100.09 [77, 123]	***	180.07 [54, 306]	***	61.44 [45, 78]	***
US	−36.16 [-50, -22]	***	−43.17 [-77, -9]	***	−38.42 [-50,-27]	***
EU	−21.91 [-36, -8]	***	−26.67 [-65, 11]	*	−25.99 [-38,-13]	***
OptOut	−152.36 [-173,-132]	***	−574.60 [-898,-251]	***	−44.98 [-54,-36]	***
Class Prob.	NA		55%		45%	

[1] The 95 percent confidence intervals obtained using the Delta Method are shown in [].
[2] Significance at the 1%, 5%, and 10% level are indicated by ***, **, and *, respectively.
[3] n = 505 and i = 4526

Table 7: Regional Interactions RPL Model Results

	Base: Beijing[1,2,3]	Shanghai	Chengdu	Guangzhou
Brand	0.384 (0.083)***	0.151 (0.109)	0.061 (0.118)	0.266 (0.112)**
Quality	0.298 (0.073)***	0.216 (0.097)**	0.050 (0.100)	0.327 (0.099)***
Certified	0.736 (0.096)***	-0.022 (0.124)	0.202 (0.134)	-0.109 (0.125)
US	−0.567 (0.107)***	0.322 (0.131)***	0.336 (0.146)**	0.514 (0.139)***
EU	−0.401 (0.105)***	0.293 (0.129)**	0.073 (0.145)	0.542 (0.137)***
OptOut	−2.249 (0.163)***			
Price	−0.015 (0.001)***			
S.D.(Brand)	0.558 (0.049)***			
S.D.(Quality)	0.442 (0.058)***			
S.D.(Certified)	0.599 (0.078)***			
S.D.(US)	0.933 (0.059)***			
S.D.(EU)	0.780 (0.062)***			
S.D.(OptOut)	2.269 (0.131)***			

[1] Standard errors shown in parenthesis ().
[2] Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 8: Regional Willingness to Pay

	Base: Beijing[1,2,3]	Shanghai	Chengdu	Guangzhou
Brand	69.29[56, 86]***	73.31[53, 98]***	61.16[37, 85]***	88.98[66,117]***
Quality	61.72[48, 77]***	69.80[50, 93]***	48.02[28, 70]***	85.54[63,111]***
Certified	103.03[81,129]***	97.69[71,130]***	128.51[95,168]***	86.13[61,116]***
US	-36.43[-52,-22]***	-33.32[-57,-11]***	-32.51[-60, -5]***	-6.77[-34, 18]
EU	-23.15[-38, -9]***	-15.4[-38, -9]*	-46.18[-76,-17]***	19.25[-6 ,44]*

[1] Standard errors shown in parenthesis ().
[2] Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 9: Demographic Interactions RPL Model Results and Willingness to Pay

	Coefficients[1,2,3]		WTP
Brand	0.382	(0.123)***	71.92[58, 88]***
Brand x Age	0.005	(0.003)*	79.31[60, 101]***
Brand x Child	-0.099	(0.078)	39.68[-1, 79]**
Brand x Migrant	-0.058	(0.089)	44.84[12, 81]***
Brand x High Income	0.014	(0.092)	55.54[17, 93]***
Quality	0.365	(0.115)***	61.82[49, 76]***
Quality x Age	0.004	(0.003)	69.54[53, 88]***
Quality x Child	-0.083	(0.069)	39.22[3, 74]**
Quality x Migrant	-0.256	(0.080)***	14.86[-16, 46]
Quality x High Income	0.195	(0.086)**	78.47[42, 116]***
Certified	1.231	(0.138)***	106.78[87, 131]***
Certified x Age	-0.010	(0.004)***	124.32[100, 154]***
Certified x Child	-0.190	(0.081)**	145.77[98, 199]***
Certified x Migrant	-0.110	(0.091)	157.28[111, 208]***
Certified x High Income	-0.085	(0.095)	159.76[112, 216]***
US	-0.025	(0.139)	-32.71[-48, -19]***
US x Age	-0.007	(0.004)*	-37.16[-57, -17]***
US x Child	0.032	(0.096)	0.08[-44, 45]
US x Migrant	-0.153	(0.108)	-25.12[-72, 21]
us x High Income	0.260	(0.114)**	31.75[-12, 77]*
EU	0.034	(0.144)	-19.20[-35, -5]***
EU x Age	-0.007	(0.004)*	-28.03[-50, -7]***
EU x Child	0.090	(0.093)	17.27[-28, 59]
EU x Migrant	-0.145	(0.110)	-15.80[-60, 27]
EU x High Income	0.283	(0.112)***	43.37[0, 87]**
OptOut	-2.168	(0.146)***	-150.95[-170, -134]***
Price	-0.014	(0.001)***	
S.D.(Brand)	0.553	(0.049)***	
S.D.(Quality)	0.409	(0.050)***	
S.D.(Certified)	0.553	(0.070)***	
S.D.(US)	0.965	(0.076)***	
S.D.(EU)	0.806	(0.081)***	
S.D.(OptOut)	2.210	(0.119)***	

[1] Standard errors shown in parenthesis () and 95% confidence intervals shown in brackets [].
[2] Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 10: Behavior Interactions RPL Model Results and Willingness to Pay

	Coefficients[1,2,3]		WTP
Brand	0.603	(0.085)***	74.14[59, 91]***
Brand x Always Order Duck	0.169	(0.140)	106.64[65, 157]***
Brand x Order Whole Ducks	-0.012	(0.080)	81.34[55, 111]***
Brand x Average Price Paid	-0.001	(0.001)	73.80[55, 97]***
Brand x Never Dine in Group >2	-1.501	(0.697)**	-127.37[-315, 58]*
Quality	0.457	(0.079)***	61.33[48, 78]***
Quality x Always Order Duck	0.120	(0.128)	80.07[40, 123]***
Quality x Order Whole Ducks	-0.040	(0.071)	57.83[35, 83]***
Quality x Average Price Paid	0.000	(0.001)	63.24[46, 84]***
Quality x Never Dine in Group >2	0.089	(0.534)	75.41[-71, 227]
Certified	1.069	(0.092)***	104.38[83, 130]***
Certified x Always Order Duck	-0.598	(0.153)***	64.87[19, 113]***
Certified x Order Whole Ducks	-0.154	(0.088)*	126.59[93, 166]***
Certified x Average Price Paid	-0.004	(0.001)***	122.18[96, 154]***
Certified x Never Dine in Group >2	-0.988	(0.651)	15.61[-169, 199]
US	-0.033	(0.096)	-36.81[-53, -22]***
US x Always Order Duck	0.065	(0.163)	4.01[-43, 53]
US x Order Whole Ducks	-0.108	(0.095)	-18.92[-49, 10]
US x Average Price Paid	-0.004	(0.001)***	-29.68[-49, -10]***
US x Never Dine in Group >2	0.710	(0.765)	96.91[-111, 312]
EU	-0.053	(0.096)	-24.84[-41, -10]***
EU x Always Order Duck	0.151	(0.156)	13.83[-31, 62]
EU x Order Whole Ducks	-0.057	(0.090)	-14.88[-45, 12]
EU x Average Price Paid	-0.002	(0.001)	-22.69[-42, -3]***
EU x Never Dine in Group >2	1.424	(0.730)**	189.89[-13, 403]**
OptOut	-2.227	(0.164)***	-153.38[-178,-133]***
Price	-0.015	(0.001)***	
S.D.(OptOut)	2.294	(0.131)***	
S.D.(Brand)	0.573	(0.050)***	
S.D.(Quality)	0.457	(0.062)***	
S.D.(Certified)	0.564	(0.081)***	
S.D.(US)	0.956	(0.059)***	
S.D.(EU)	0.802	(0.062)***	

[1] Standard errors shown in parenthesis () and 95% confidence intervals shown in brackets [].
[2] Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 11: Attribute Interactions RPL Model Results and Willingness to Pay

	Coefficients[1,2,3]		WTP
Brand x US	0.317	(0.065)***	42.82[25, 62]***
Brand x EU	0.415	(0.079)***	55.57[36, 75]***
Brand x China	0.662	(0.064)***	89.33[69, 114]***
Quality x US	0.351	(0.059)***	47.22[32, 64]***
Quality x EU	0.470	(0.062)***	63.52[47, 82]***
Quality x China	0.384	(0.058)***	51.59[35, 69]***
Certified x US	0.679	(0.072)***	92.14[67, 122]***
Certified x EU	0.700	(0.075)***	94.41[68, 123]***
Certified x China	0.768	(0.066)***	103.36[80, 131]***
OptOut	-5.710	(0.252)***	-384.61[-451,-333]***
Price	-0.015	(0.001)***	
S.D.(Brand x US)	0.799	(0.088)***	
S.D.(Brand x EU)	0.383	(0.109)***	
S.D.(Brand x China)	0.865	(0.084)***	
S.D.(Quality x US)	0.637	(0.079)***	
S.D.(Quality x EU)	0.443	(0.086)***	
S.D.(Quality x China)	0.599	(0.083)***	
S.D.(Certified x US)	0.907	(0.109)***	
S.D.(Certified x EU)	0.964	(0.122)***	
S.D.(Certified x China)	0.722	(0.096)***	
S.D.(OptOut)	3.284	(0.243)***	

[1] Standard errors shown in parenthesis () and 95% confidence intervals shown in brackets [].
[2] Significance at the 10%, 5%, and 1% level are indicated by *, **, and ***, respectively.
[3] n = 505 and i = 4526

Table 12: Individual WTP Regression Coefficients and Standard Errors

	Brand	Quality	Certified	US	EU
Shanghai	0.066(0.039)*	0.047(0.028)*	0.027(0.038)	0.200(0.073)***	0.177(0.062)***
Chengdu	0.027(0.042)***	0.013(0.030)	0.050(0.040)	0.102(0.079)	0.072(0.067)
Guangzhou	0.111(0.041)	0.103(0.029)***	0.004(0.039)	0.263(0.077)***	0.249(0.065)***
Always Dine in Group	0.412(0.217)*	0.141(0.155)	0.404(0.208)*	-0.243(0.407)	-0.243(0.344)
Sometimes Dine in Group	0.433(0.218)**	0.143(0.156)	0.450(0.210)**	-0.054(0.410)	-0.085(0.347)
Rarely Dine in Group	0.331(0.225)	0.085(0.161)	0.404(0.216)*	-0.168(0.422)	-0.191(0.358)
Average Price Paid	-0.001(0.001)*	0.000(0.000)*	-0.001(0.000)	-0.002(0.001)*	-0.001(0.001)*
High Income (>150 k/yr)	0.011(0.034)	0.041(0.025)	-0.007(0.033)	0.141(0.064)**	0.123(0.054)**
Income Increased (2yrs)	-0.009(0.029)	0.017(0.021)***	0.017(0.028)	0.076(0.054)	0.055(0.046)
Migrant (2 yrs)	-0.054(0.032)*	-0.078(0.023)	-0.045(0.031)	-0.133(0.061)**	-0.112(0.051)**
Constant	0.019(0.225)	0.227(0.161)	0.236(0.217)	-0.109(0.423)	0.005(0.358)
R^2	0.0465	0.0757	0.0323	0.0826	0.0902
F	0.0111	0.0000	0.1054	0.0000	0.0000

Results align nicely with the each of the RPL models' results. For example, the regressions indicate that being from Shanghai and Guangzhou positively contributes to WTP for imported biotechnology. Being from a high income group increased WTP for imported biotechnology. Also, dining in groups larger than two more often positively contributes to WTP for branded and certified duck entrees. Finally, migrants tend to be less willing to pay for imported biotech and brand.