Decision-Making in the Livestock Supply Chain

by

Shijun Gao

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved October 2022 by the
Graduate Supervisory Committee:

Carola Grebitus, Chair
Troy Schmitz
Karen DeLong

ARIZONA STATE UNIVERSITY

December 2022

ABSTRACT

Decision-making is critical in the livestock supply chain. Understanding how producers and consumers make their decisions requires a sufficient understanding of the process of their decision-making behavior. Based on the processing resources, consumers or producers' choices could be affected by different processes: affective process, cognitive process or both affective and cognitive processes simultaneously. Applying a variety of experiment methods, this dissertation investigates how producers and consumers make their choices by exploring how the product attributes, and the characteristics of the decision-maker, affect consumers and producers' choice-making behaviors. In the first essay, I implemented a discrete choice experiment and estimated random parameter logit models with error component to analyze Chinese consumer willingness to pay (WTP) for domestic and imported beef flank labeled with the new quality grades and other relevant beef labels. Results suggest foreign beef producers could compete most closely with domestic beef if it was labeled as premium quality.

In the second essay, I investigate Chinese consumer WTP for beef from different countries and the role of ethnocentrism, country image, and product image on the WTP. Results suggest that foreign beef exporters could promote their beef in China by advertising in accordance with positive country and product images.

In the third essay, I attempt to determine hog farmers' motivations to adopt genomics for breeding hogs that are more resistant to the disease. In doing so I focus on the impact of their risk preferences and related peer effects that might influence potential adoption. This case study provides implications for local governments and companies trying to promote new technologies.

In the fourth essay, I investigate how social influence affects producers' behavior under disease outbreak using social network analysis. In particular, I focus on how information flows during an epidemic such as African Swine Fever. Findings provide insights into how information flows and how actors communicate during a situation of crisis. This can be used by stakeholders (1) to disseminate information; and (2) to avoid the spread of rumors and false information.

Dedicated to My Parents

ACKNOWLEDGMENTS

Pursing this Ph.D. was a lifelong dream for me and became a truly life-changing experience. I greatly appreciate all the support and encouragement that I have received during this extraordinary journey.

First and most importantly, I would like to thank my esteemed supervisor and mentor – Dr. Carola Grebitus. She has demonstrated great commitment to my work by spending countless hours with me – from idea generating to journal review processes. Outside of the classroom, she also provides a lot of support and it is evident that she cares about her students. To me she is a brilliant academic, a considerate and thoughtful thesis advisor, a great friend and a life mentor!

I also greatly appreciate all the support and guidance from the rest of my fantastic committee members: Dr. Troy Schmitz and Dr. Karen DeLong. Thank you to Dr. Troy Schmitz, who provided incredible support and guidance not only on my dissertation but also on my academic career. In addition, thank you to Dr. Karen DeLong, who always took the time to answer my questions.

I am also grateful for the help and guidance I received from other members in the Morrison School of Agribusiness. Thanks to Dr. Timothy Richards and Dr. Jeffrey Englin. Taking their Ph.D. courses provided me with rigorous training on methodology. Thanks to Dr. Ashok Mishra, Dr. Renee Hughner, Dr. Mark Manfredo, Dr. Alexis Villacis Aveiga, Dr. David Van Fleet and Dr. Lauren Chenarides; working with them as a teaching assistant was a great experience during my PhD journey. I am also grateful for the amazing administrative assistance from Karen Rodriguez, Cindy Jauch and Hilda Olsen.

I would also like to thank all my friends and officemates in the Ph.D. students' office during this journey, including but not limited to Alwin, Malu and Kathy. Thanks for your company and care. I will never forget the time we had together. I also want to thank all my friends from ASU, especially Lei, Yiwen, Di, Weining, Guang, Weixiang and Shengdong. Thank you for your company and care. You taught me a lot and helped me grow. My PhD life was much better because of you.

Last but not least, I would also like to thank my family, to whom this dissertation is dedicated. My father, Shenggan Gao, and my mother, Yan Ran, who are behind every one of my decisions. They have been giving me all their love and showing me there is always a home.

TABLE OF CONTENTS

CHAPTER Page

APPENDIX Page

LIST OF TABLES

Table Page

Table Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Decision-making is a core issue in the livestock supply chain for producers and consumers. The main decisions that producers make include, for example, whether to continue producing a certain product, or whether to adopt new technologies. The latter of the two questions is highly associated with the production efficiency of a livestock producer since technology is a main factor in the production function. At the same time, consumers need to choose which food product to purchase in their daily lives. Their choices are informed by consumer theory where the fundamental idea is that consumers make a choice based on their preferences. In other words, consumers always choose the alternative which gives them the highest utility. Further, the theory of value and random utility theory inform studies of decision-making (Lancaster, 1966; McFadden, 1974). According to these theories, consumers' utility is obtained based on a product's sub-utilities for its separable characteristics or attributes. With regards to food, consumers pay attention to a number of product characteristics, such as, price, quality grade or country of origin (Lusk and Briggeman, 2009). Moreover, besides the product characteristics, affective processes also play an important role in consumers' product evaluation (Tomer, 2017; Grebitus and Van Loo, 2022). For instance, Verlegh and Steenkamp (1999) divided Country-of-origin (COO) effects into three components: cognitive, affective, and normative. The cognitive aspect of COO labels conveys food quality information to consumers (Grebitus, 2008; Caputo et al., 2017). The affective aspect refers to symbolic and emotional values that COO labels evoke in consumers, such as social status and national pride. Social and personal norms related to COO labels, such as, ethnocentrism and patriotism belong to the normative component (Ehmke et al., 2008; Verlegh and Steenkamp, 1999).

The livestock supply chain is an important part of the global food system contributing 40% of the global value of agricultural output and supporting the livelihoods and food of almost 1.3 billion people (World Bank, 2022). Pork and beef are two main types of livestock. The USDA (2022) forecasts global pork and beef production in 2023 to reach 111 million tons and 59 million tons, respectively. Both pork and beef are dominant animal-protein sources in the Chinese diet. In 2019, Chinese people ate 44,866 metric tons of pork, covering 45% of the global pork consumption (USDA, 2021). Chinese people also ate 9,486 metric tons of beef in 2019 meaning that China ranks 2nd in beef consumption globally after the U.S. (OECD, 2019; USDA, 2021). Livestock, including pork and beef, is also important to other countries, such as, the United States (U.S.). The U.S. is one of the largest beef exporters in the world, with US beef exports valued at a record $8 billion in 2018 (U.S. Meat Export Federation, 2019a). That year, beef exports accounted for nearly 15% of total beef production and added $323 per head of fed slaughter (U.S. Meat Export Federation, 2019b). Given the importance of the livestock supply chain, Chapters 1 and 2 focus on consumer beef choices and Chapters 3 and 4 focus on hog producer decision making.

Hence, in my dissertation I add to the understanding of how producers and consumers make their decisions by exploring how the attributes from the product (e.g., price, quality grades), and the characteristics of the decision-maker (e.g., risk preferences, ethnocentrism) affect their choices.

In the first chapter, I estimate consumers' valuation of a novel beef quality grading system in China using consumer choice experiments with shelf simulation. To do so, I explore the willingness to pay (WTP) for beef flank carrying quality grades. In addition, I test WTP for beef originating from different countries, as well as, beef carrying different organic labels. Results show Chinese consumers are willing to pay an extra ¥80/kg to ¥100/kg for beef flank carrying a Premium quality grade compared to ungraded beef. However, consumers discounted Regular graded beef by ¥ -30/kg to ¥ -50/kg compared to beef without quality grade information. Results also suggest consumers prefer domestic beef compared to foreign beef from the U.S., Australia and Brazil. More specifically, results indicate consumers prefer Australian beef compared to beef from Brazil or the U.S., and they value US beef similar to Brazilian beef. Moreover, imported beef was valued higher if it was graded as Premium quality. However, WTP estimates were more negative for imported beef if it was graded as Regular quality. Results of this chapter could be used by the Chinese government to modify the new grading system further, and beef producers and retailers could refer to these results to understand how consumers value such grades and how to market their products.

The second chapter studies Chinese consumers' ethnocentrism levels and their perceptions of major beef exporting countries and beef products from associated countries. I used a choice experiment to analyze how ethnocentrism and perception affect WTP for beef from different countries. Results reveal Chinese consumers have heterogenous preferences for beef based on their perceived image of the beef's country of origin and beef safety. Also, the more ethnocentric consumers are, the more they are willing to pay for domestic beef and the more they discount foreign beef. Furthermore, results indicate that consumers are willing to pay a premium for imported beef if they are more in favor of the country from where the beef originates or perceive the beef from the country of origin as safer. These results are critical for foreign beef exporters to execute their marketing strategies. More specifically, beef exporters from the U.S., Australia, and Brazil could try to attract Chinese consumers by emphasizing positive country or safety images associated with their country to expand their market share in China and strengthening their exports.

The third chapter investigates hog farmers' motivations to adopt genomics technology to prevent African Swine Fever. More specifically, I focused on the impact of farmers' risk preferences, attitudes and social networks on genomics adoption. Genomics technology is used for breeding hogs that are more resistant to African Swine Fever. To collect my data, I conducted face-to-face interviews with hog farmers in China in 2019. Results from social network analysis indicate hog farmers' social network status, such as, centrality does not affect the time frame to adopt the technology. However, the time frame that hog farmers prefer to adopt the technology is correlated with their peers' time frames. Results also suggest that hog farmers form networks with other farmers who are similar to them, and share similar attitudes in adopting genomics, as well as having similar risk preferences. Results from this case study provide implications for local governments and companies trying to promote new technologies.

In the fourth chapter, I investigate how social influence affects hog producers' behavior under disease outbreaks using social network analysis. More specifically, the analysis focuses on how information flows during an epidemic, such as, African Swine Fever. The results show that hog farmers meet a lot less in person with other hog farmers and sales agents after an outbreak but use text or phone calls more often. Interestingly, the frequency of face-to-face meetings with veterinarians remains the same, which suggests that the desire to have less face-to-face meetings is replaced with the demand for more help from veterinarians regarding hog health. The findings provide insights into how information could be disseminated more effectively and efficiently. Local governments could use these results to disseminate important information to hog producers and avoid the spread of rumors and false information in an effective and efficient way.

The final chapter summarizes my empirical findings and provides implications of my research. My findings contribute to the understanding of how consumers and producers make their choices in the livestock supply chain. In particular, my results shed light on how the attributes of the product and the characteristics of the decision-maker affect their behavior. Findings of my dissertation not only offer implications to the government on promoting new food labels and technologies, but also provide insights to food retailers on expanding their business in the food market. Finally, I provide suggestions for future work emphasizing effects of psychological processes, such as, ethnocentrism on product valuation, and generalizing my empirical results to other food sectors.

CHAPTER 2

CONSUMER PREFERENCES FOR BEEF QUALITY GRADES ON IMPORTED AND DOMESTIC BEEF

2.1. Introduction

Food certifications play a critical role in providing quality-related information to consumers, and decreasing information asymmetry between consumers and producers (Balogh et al., 2016; Caswell and Mojduszka, 1996). Governments often assist in making information accessible to consumers, for example, by creating and regulating food labeling programs (Caswell and Mojduszka, 1996). In China, rising incomes have led to an increased demand for food quality (Xinhua News, 2019; Zipser and Poh, 2021; Leung et al., 2020; Gale and Huang, 2007). Therefore, over the past decade the Chinese government has instituted several quality grade systems for food products in an attempt to improve the quality of agricultural products (Nie et al., 2020; Nie et al., 2021). However, many of these quality grade systems have not been well adopted in the retail market for various reasons, including insufficient market demand and ineffective regulation (Nie et al., 2020; Nie et al., 2021).

China did not begin researching a quality grade standards system for beef until 2000 (Chen et al., 2012). In an evaluation of domestic beef, Zhou (1998) concluded that the Chinese Ministry of Agriculture and Rural Affairs needed to develop a universal beef grade system similar to the United States Department of Agriculture (USDA) beef grading system. In 2003, China implemented their first beef quality grade system and modified this in 2012 (National Public Service Platform for Standards Information (NPSP), 2021b). However, similar to other Chinese quality grade programs (Nie et al., 2020; Nie et al., 2021), most retail beef is currently not labeled with quality grades due to complications with implementation (NPSP, 2021b). Therefore, this policy is currently undergoing another revision which was drafted in April 2020, was approved in August 2021, and will soon be implemented (NPSP, 2021a). According to the Chinese Ministry of Agriculture and Rural Affairs, this updated version will make carcass grading more consistent with beef quality grading systems in the United States, Australia, Japan, and South Korea with the objective of incentivizing high quality domestic beef production in China (NPSP, 2021b). The goal of this research is to evaluate this policy and its implications by estimating Chinese consumer preferences for this beef quality grade system.

Beef is an important emerging animal protein source in China, partially because of improved Chinese incomes (Gale and Huang, 2007; Beef Magazine, 2021). From 2018 to 2019, overall Chinese beef consumption increased by 13% and reached 8.8 million metric tons (MTs), ranking second in the world after the United States (US) (USDA, 2022). By 2021, beef consumption increased further and reached 9.8 million MTs (USDA, 2022) (Figure 2.1). Chinese per capita beef consumption increased from 3.6 kg in 2018 to 4.1 kg in 2021 (OECD, 2021). This 14% increase in per capita consumption marked a large increase in the last three years and was partially motivated by the outbreak of African Swine Fever (ASF) which dampened pork sales in 2018 (USDA, 2019). It is anticipated that the demand for beef in China will continue strongly into the future (Beef Magazine, 2021).

While beef consumption has increased steadily in China, the domestic production of beef has remained constant at around 6.8 million MTs (USDA, 2022) (Figure 2.1). Thus, Chinese beef imports are responsible for satisfying the increased Chinese demand for beef and have expanded from being a negligible amount prior to 2013 to 3 million MTs in 2021 (USDA, 2022) (Figure 2.1). China is the largest beef importer in the world and now the destination for 30% of the world's beef exports; a percentage which has grown for the ninth consecutive year since 2012 (USDA, 2022). Provided the recent growth of the Chinese beef market, it is important to understand the factors affecting Chinese consumer demand for both domestic and imported beef.

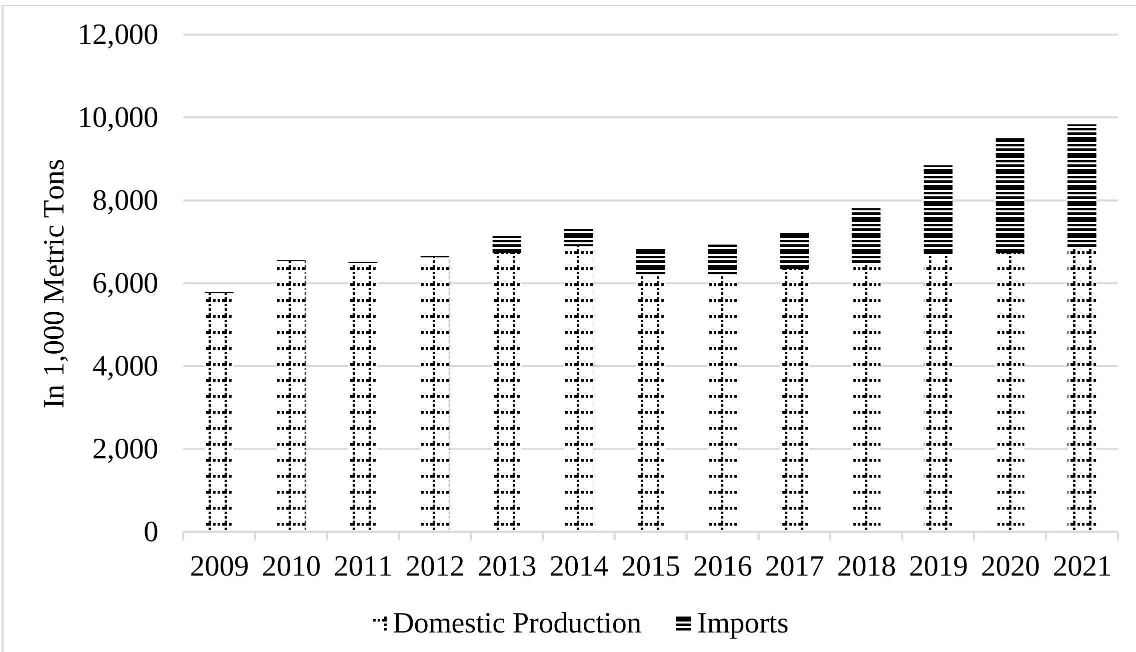


Figure 2.1. Chinese Beef Production and Imports Quantities from 2009 to 2021
Notes: Consumption= Production + Imports (USDA, 2022)

Against this background, the goal of this study is to determine how the Chinese beef quality grade system will affect Chinese consumer preferences for beef in a retail environment. To accomplish this, we will use a shelf-simulation choice experiment to elicit Chinese consumer willingness to pay (WTP) for beef labeled with varying quality grades. China imports a large share of beef (USDA, 2022); therefore, we also consider how beef quality affects Chinese consumer preferences for imported beef. Additional quality-relevant cues (e.g., Green Food label, Organic label) are included in the choice experimental design given previous research has found that they affected Chinese consumer preferences for beef (Ortega et al., 2016).

The beef product used in the choice experiment is beef flank because it is one of the primary beef products consumed in China. The different quality grades used to regulate beef flank are “Premium” and “Regular”. Premium signifies the highest quality beef product while Regular signifies a slightly lower quality product. This study will contribute to the literature by analyzing the effectiveness of quality grade systems in China and by analyzing how Chinese demand for foreign beef is influenced by beef quality.

Previous research has primarily evaluated Chinese consumer preferences for pork (Ortega et al., 2017; Yu et al., 2014; Ortega et al., 2011) but more recently has also examined Chinese consumer preferences for beef (Lin et al., 2020; Ortega et al., 2016). Lin et al. (2020) conducted a choice experiment and found that Chinese beef consumers were willing to pay a premium for beef flank with a blockchain traceability label. They also found that Chinese consumers were willing to pay more for Australian beef than domestic beef but were not willing to pay premiums for Canadian or US beef. Ortega et al. (2016) found that Beijing consumers were willing to pay more for beef quality indicator labels, such as, Organic certification and the Green Food label. They also found that Chinese consumers would pay more for Australian beef than domestic or US beef. While these studies have examined aspects of Chinese consumer preferences for beef, this study contributes to the literature by examining Chinese consumer preferences for beef quality grades and how beef quality impacts demand for imported beef.

2.2. Previous Literature on Quality Grades

Previous research has investigated Chinese consumer preferences for quality grades for apples (Nie et al., 2021) and rice (Nie et al., 2020). Nie et al. (2021) conducted a choice experiment to determine Chinese consumer WTP for quality graded Fuji apples. They found consumers had significant and positive WTP estimates for Fuji apples labeled as "Super" and "Good", with apples labeled as "Super" receiving the highest WTP. Nie et al. (2020) did a general survey of Chinese consumers to elicit their knowledge about an existing rice grading system. They found that consumer trust and knowledge of the rice grading system affected consumer concerns regarding quality grades in their purchasing decisions. With respect to Chinese beef quality grades, Liang et al. (2016) did a sensory analysis to determine how taste ratings for fattened yellow crossbred steers corresponded with quality grades. They found that taste ratings increased as quality grade level increased. To the best of our knowledge, these studies are the only articles examining Chinese consumer preferences for quality grades. Thus, this research will contribute to the literature by evaluating Chinese consumer WTP for beef labeled with different quality grades.

Outside of China, several studies have investigated how quality grade information affects consumer WTP for meat. Abidoye et al. (2011) and Palma et al. (2018) found that US consumers were willing to pay more for USDA Choice beef than for the USDA Select beef. With regards to quality grading, research by Chung et al. (2009) suggested that Korean consumers were willing to pay a premium for the marbling of beef either graded as extra premium, premium, or Grade A compared to Grade C marbled beef. Lusk et al. (2018) found that pork quality grade information could increase pork chop sales. Merritt et al. (2018) stated that US consumers were willing to pay a premium for beef steak carrying a Master Quality Raised Beef label. Research by Lewis et al. (2017) indicated that consumers in the UK and Germany were willing to pay more for beef with the “Little Red Tractor” and “Quality and Safety” quality assurance seals, respectively. Balcombe et al. (2016) found UK consumers were willing to pay more for beef steak carrying an International quality label. Given that consumers typically are willing to pay more for superior quality beef, we hypothesize that Chinese consumers will pay more for domestic and foreign beef that is of superior quality.

2.3. Methodology

2.3.1. Study Design

To elicit Chinese consumers’ WTP for imported and domestic beef with varying quality information we surveyed 560 consumers in the three major Chinese cities Beijing, Shanghai, and Guangzhou in the summer of 2021. We focused on these cities because they are considered to be three of the most economically important cities in China (Deloitte, 2010; Bin, 2021). The survey instrument was pre-registered on aspredicted.org. The study was considered exempt by the ethics board (IRB) of a large Southwestern University in the U.S. The survey was programmed in Qualtrics and data were collected through Qualtrics.

2.3.2. Choice Experiments

To elicit Chinese consumer WTP for the new beef quality grades, we used choice experiments as they remain one of the most widely used techniques to analyze stated preferences in ex-ante studies, where new products and attributes are introduced to the market. In applying choice experiments, respondents are asked to choose their most preferred alternative from several products and one “none-of-these” option in each choice task. Each alternative is composed of several attributes characterized by different levels.

The beef product investigated was beef flank ("牛腩" in Chinese), because it is one of the most common beef cuts in China. The attributes included in the choice experiment appear in Table 2.1 and include: price, country of origin labels (COOLs), Chinese quality grades, and other relevant government regulated labels.

Table 2.1. Attributes and Attribute Levels in the Choice Experiment

Attribute	Price / kg	Country of origin	Quality grade	Government Programs
Level	56 Yuan / kg	China (中国)	Premium (优级)	Organic (有机食品)
	86 Yuan / kg	US (美国)	Regular (普通级)	Green-Food[1] (绿色食品)
	116 Yuan / kg	Australia (澳大利亚)	No label	No label
	146 Yuan / kg	Brazil (巴西)		

The price levels were chosen based on market observations and beef prices from the Beijing Municipal Price Supervision Center (2021). Following the most recent Chinese quality grade guidelines, the two quality grade labels for beef flank are Premium and Regular (NPSP, 2021c). The Premium quality grade signifies a specific lean coloring, and it must have marbling. To qualify as Regular, the beef flank must constitute a specific lean color (which is of lower quality than the lean color required for the Premium grade) and does not require any marbling (NPSP, 2021c). The countries included in the choice experiment are China, the US, Australia, and Brazil. Brazil was included since they are consistently the largest beef exporter to China and accounted for 41% of the value of Chinese beef imports in 2020 (China Customs Statistics, 2021). Australia was chosen since

[1] Similar to the Organic label, the Green-Food label is widely used in many food products in China, such as, beef, rice, milk.

they accounted for nearly 15% of the value of China's beef imports in 2020 and are typically the second or third largest beef exporter to China. The US was included since China reopened their market to US beef imports in 2017 following a BSE-related ban that began in 2003 (Reuters, 2020). The US, while only accounting for two percent of China's beef imports in 2020, is an important emerging supplier of beef. For example, through October 2021, the US had supplied China with 10% of the value of their 2021 beef imports (China Customs Statistics, 2021). The choice experimental design utilizes interaction terms between each country and each quality grade to examine how the quality of foreign beef influences Chinese consumer preferences.

In terms of other relevant Chinese government regulated labels, we follow Ortega et al. (2016) and include the Green Food and Organic labels (Figure 2.2). The Chinese government manages a two-level food certification system to ensure food safety: Green Food Certification and Organic Food Certification (Yu et al. 2014). Green Food is a unique certification in China, managed by the Chinese Green Food Development Center under the Ministry of Agriculture and Rural Affairs. Green Food certification is widely used in many Chinese food products including beef, rice, milk, and tea. The Chinese government realized that most food products in China, a developing country, cannot adhere to the stringent standards of organic food elsewhere. Hence, they developed a less stringent certification that includes limited use of pesticides, chemical fertilizers, and other chemical inputs to fulfill market demand (Yu et al., 2014). The official definition of Green Food is as follows:

"Under strict supervision, control and standard production in production, processing, packing, storage and transportation, Green Food adopts the whole-some quality control from farm to table, while it requires reasonable applications of inputs, including pesticides, fertilizers, veterinary drugs and additives etc., to prevent any pollution of toxic and harmful matters to produce and process food so as to ensure environmental and product safety" (China Green Food Development Center, 2011).

The Organic food label is the most stringent organic certification in China, and has a similar definition and standard as other countries. On January 1st, 2020, China implemented revised organic certification rules and updated the 2011 published national standard for organic products (USDA, 2019). The new organic standard includes changes to production and processing inputs, such as, adjusting lists of food additives, and changing the requirements for labeling organic conversion products (USDA, 2019). Before answering each choice task, participants were provided with definitions of all attributes and received a description of the different proposed quality grades. This information appears in the appendix (see appendix A, Information sheet for participants).

Green Food Label	**Organic Label**
绿色食品®	中国有机产品 ORGANIC

Figure 2.2. Green Food and Organic Labels

To display the choice tasks, shelf simulation of packages containing 1.150 kg of beef flank were used. Each choice task contained premium photographs of three alternatives of beef flank characterized by the attributes. Participants had to choose either one of the three beef flank options (see Figure 2.3 for an example) or neither of the options.

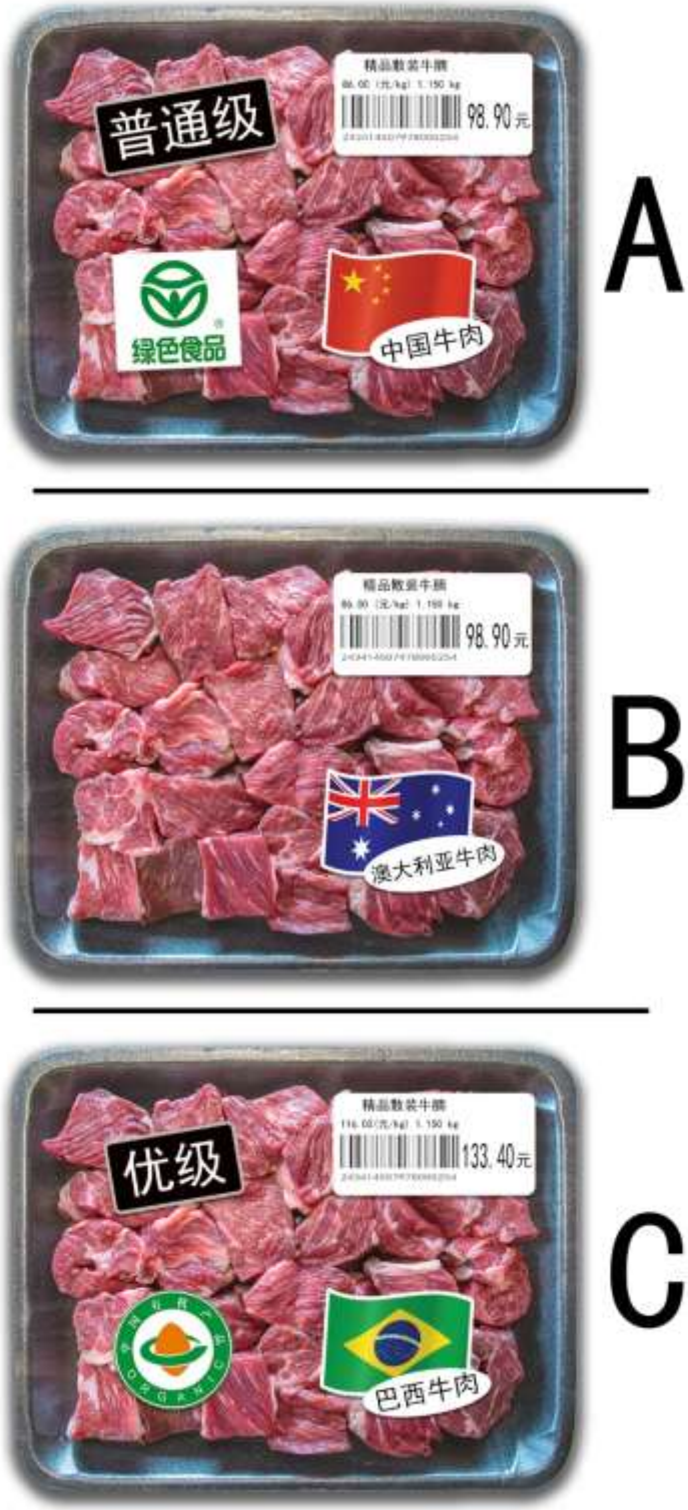


Figure 2.3. Example Choice Task

To create the choice tasks, an efficient experimental design following Street and Burgess (2007) was programmed using NGene (ChoiceMetrics, 2021). To create the efficient design, a sequential-stage approach was utilized following Scarpa, Campbell and Hutchinson (2007a) and Scarpa et al. (2013). In the first stage, an Optimal Orthogonal in the Differences (OOD) choice experimental design was created with 36 choice tasks. Participants from a pretest completed these choice tasks and this data was used to estimate a multinomial logit (MNL) model. In the second stage, the coefficient estimates from the MNL model in the pretest were included as prior information to generate an efficient design. In addition, priors for the interaction terms were included following a uniform distribution from -0.5 to 0.5. The efficient design minimizes the standard errors of the parameter estimates by using the prior information on the parameters from the pretest (ChoiceMetrics, 2021). The chosen efficient design was selected because it had the lowest D-error, which indicates it is the most efficient given the number of choice tasks and blocks (ChoiceMetrics, 2021).

The final efficient design resulted in 36 choice tasks grouped into three blocks with 12 choice tasks in each block. Only one randomly chosen block with 12 choice tasks was presented to each respondent to avoid fatigue effects (Bradley and Daly, 1994; Savage and Waldman, 2008; Hess et al., 2012). The order of the 12 choice tasks in each block was randomized to avoid ordering effects (Carlsson et al., 2012). Prior to making the choices, we provided a cheap talk script to reduce hypothetical bias (Lusk, 2003; Tonsor and Shupp, 2011).

2.3.3. Random Parameters Logit Model

The random parameter logit (RPL) model was used to analyze the choice experiment data. We used the RPL, or mixed logit model, because it allows for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2009). The derivation of the RPL begins by assuming a linear form of the utility function for individual i choosing beef alternative j at time t:

$$U_{ijt} = \beta_i * X_{ijt} + \epsilon_{ijt} \tag{1}$$

where X_{ij} are independent and observed factors associated with beef alternative j and individual i at time t including COOLs, price, quality grades, and organic labels. ϵ_{ijt} is an unobserved random error term that is assumed to be independently and identically distributed and follows the Gumbel distribution. β_i is a vector of coefficients of different beef attributes for individual, i, representing their tastes. β_i is a vector of random variables with density function of $f(\beta_i \mid \theta)$, while θ represents the parameters with respect to the density function. For example, θ represents the mean and variance if β_i is normally distributed. Following Train (2009), the probability of individual i choosing alternative j is:

$$P_{ijt} = \int \frac{e^{\beta_i X_{ijt}}}{\sum_j e^{\beta_i X_{ijt}}} f(\beta) d\beta \tag{2}$$

All parameters except price are assumed to be independent normally distributed while the price coefficient is assumed to be fixed for all individuals in order to guarantee that the WTP for each non-price attribute has the same normal distribution. The RPL model was estimated through the simulated maximum likelihood method with 500 Halton draws following Train (2009).

2.3.4. RPL Model with Error Component

In addition to estimating the RPL model, we also estimated a RPL model with an error component (RPL-EC) following Scarpa et al. (2005a) and Scarpa et al. (2005b). The RPL-EC model takes into account any heteroskedasticity that may be caused by the presence of the none-of-these options appearing in each choice task compared to only a subset of product attributes appearing in each choice task following the experimental design (Caputo et al., 2013). Since the RPL-EC takes this into consideration, previous studies have found that the RPL-EC model has an improved model fit (Scarpa et al., 2007b; Scarpa and Rose, 2008; Caputo et al., 2013; Van Wezemael et al., 2014).

Similar to the RPL model**,** the derivation of the RPL-EC model begins by setting up the utility function for individual *i* choosing beef alternative *j* for time period *t* as:

$$U_{ijt} = \beta_i * X_{ijt} + \mathrm{I_j}\eta_{ij} + \epsilon_{ijt} \tag{4}$$

where the variables are the same as in equation (1) but the parameter η_{ij} is an additional zero mean error component to capture the possible heteroskedasticity which may exist due to the presence of the none-of-these options in each choice task.

By assuming that all taste parameters in β_i follow the normal distribution, and the price coefficient is non-random, the unconditional probability after integrating over both β_i and η based on the distributions f and τ for the RPL-EC is:

$$P_{ijt} = \int\int \mathrm{L_{ij}}(\beta_i, \eta_i)\tau(\eta)f(\beta_i)d\beta_i \mathrm{d}\eta \tag{5}$$

2.3.5. Utility Function

Respondents completed 12 choice tasks, where the beef flank alternatives were labeled with different attribute levels. Thus, the indirect utility function we estimated for the RPL and RPL-EC models is specified as follows:

$$U_{ijt} = \beta_p Price_{ijt} + \beta_1 Bra_{ijt} + \beta_2 Aus_{ijt} + \beta_3 USA_{ijt} + \beta_4 Premium_{ijt}$$
$$+\beta_5 Regular_{ijt} + \beta_6 Organic_{ijt} + \beta_7 GreenFood_{ijt} + \beta_8 \text{None}_{ijt} + \epsilon_{ijt} \quad (6)$$

where β_p is the price coefficient and β_{1-7} are the coefficients for all attribute levels, which are varying over individual *i*. *Bra, Aus, USA* are three dummy variables equal to one if the beef flank was labeled as originating from Brazil, Australia, or the US, respectively and zero otherwise. The base country omitted was China; thus, all COOLs were compared to China. *Premium* and *Regular* are two dummy variables that take the value of 1 if the beef flank carried the Premium or Regular quality grade, respectively, and zero if the quality grade was not present. *Organic* and *Green Food* are dummy variables equal to 1 if the Organic or Green Food label was presented on the beef flank package, respectively, and zero otherwise. β_8 is a dummy variable equal to 1 if the respondent chose the "None of these" option, 0 otherwise. ϵ_{ijt} is a random error term following the Gumbel distribution and specific to each consumer *i*. The indirect utility function estimated in the RPL-EC model is modified by changing the ϵ_{ijt} in Equation (6) to $\mathrm{I_j}\eta_{ij} + \epsilon_{ijt}$ in order to capture the potential heteroskedasticity due to the none-of-these option being in each choice task. Since the RPL-EC model is hypothesized to have a better goodness of fit than the RPL model, we proceed with RPL-EC to estimate the models that include the interaction effects.

In this model specification, we include interaction terms between COOL and the Premium and Regular Quality grades. Due to collinearity issues, we could not estimate the full interaction model. Therefore, two separate interaction models are estimated: the RPL-EC model with the Premium quality grades interacted with COOL (EC-PRE) and the RPL-EC model with the Regular quality grades interacted with COOL (EC-REG). The following equation was estimated for the EC-PRE model:

$$U_{ijt} = \beta_p Price_{ijt} + \beta_1 Bra_{ijt} + \beta_2 Aus_{ijt} + \beta_3 USA_{ijt} + \beta_4 Premium_{ijt}$$
$$+\beta_5 Regular_{ijt} + \beta_6 Organic_{ijt} + \beta_7 Greenfood_{ijt} + \beta_8 Bra * Premium_{ijt}$$
$$+\beta_9 Aus * Premium_{ijt} + \beta_{10} USA * Premium_{ijt} + \beta_{11} None_{ijt} + \mathrm{I_j}\eta_{ij} + \epsilon_{ijt} \quad (7)$$

Similarly, the following equation was estimated for the EC-REG model:

$$U_{ijt} = \beta_p Price_{ijt} + \beta_1 Bra_{ijt} + \beta_2 Aus_{ijt} + \beta_3 USA_{ijt} + \beta_4 Premium_{ijt}$$
$$+\beta_5 Regular_{ijt} + \beta_6 Organic_{ijt} + \beta_7 Greenfood_{ijt} + \beta_8 Bra * Regular_{ijt}$$
$$+\beta_9 Aus * Regular_{ijt} + \beta_{10} USA * Regular_{ijt} + \beta_{11} None_{ijt} + \mathrm{I_j}\eta_{ij} + \epsilon_{ijt} \quad (8)$$

where $\beta_8, \beta_9, \beta_{10}$ in both Equations (7) and (8) are the coefficients for the interaction terms. $Bra * Premium_{jt}$ is a dummy variable that takes the value of 1 if both "Brazil" and "Premium" labels are present on the beef package, and 0 otherwise. All other interaction variables were generated accordingly. All models (RPL, RPL-EC. EC-PRE, and EC-REG) were estimated using the software NLogit 6.0 with 500 Halton draws.

2.3.6. Willingness to Pay Calculation

The WTP for each attribute is calculated by dividing each attribute coefficient β_k by the negative of the price coefficient β_p, such that $WTP_k = \beta_k/(-\beta_p)$. The variance of the WTP of each attribute is calculated following Daly et al. (2012):

$$Var(WTP_k) = \left(\frac{\beta_k}{\beta_p}\right)^2 \left(\frac{w_{kk}}{{\beta_k}^2} + \frac{w_{pp}}{{\beta_p}^2} - 2\frac{w_{kp}}{\beta_k \beta_p}\right) \quad (9)$$

where β_k is the estimated parameter of the specific attribute, β_p is the price coefficient, and w_{kk}, w_{pp} and w_{kp} are the variance and covariance for the respective parameter estimates (Printezis and Grebitus, 2018). The interaction WTP is calculated following:

$$WTP_{\mathrm{k_1k_2}} = \frac{(\beta_{\mathrm{k_1}} + \beta_{\mathrm{k_2}} + \beta_{\mathrm{k_1k_2}})}{-\beta_{\mathrm{p}}} \quad (10)$$

where β_p is the price coefficient and $\beta_{\mathrm{k}_1\mathrm{k}_2}$ is the coefficient for the interaction term, which is either β_8, β_9 or β_{10} in equations (7) and (8). The variance of the interaction WTP is calculated following Syrengelas et al. (2018):

$$Var(WTP_{\mathrm{k}_1\mathrm{k}_2}) = \left(-\frac{1}{\beta_p}\right)^2 \left[w_{\mathrm{k}_1\mathrm{k}_1} + w_{\mathrm{k}_2\mathrm{k}_2} + w_{mm} + 2\left(w_{\mathrm{k}_2\mathrm{k}_1} + w_{m\mathrm{k}_1} + w_{m\mathrm{k}_2}\right)\right] +$$

$$\left(-\frac{1}{\beta_p}\right)\left(\frac{\beta_{\mathrm{k}_1}+\beta_{\mathrm{k}_2}+\beta_m}{(-\beta_p)^2}\right)\left[2\left(w_{p\mathrm{k}_1} + w_{p\mathrm{k}_2} + w_{pm}\right)\right] + \left(\frac{\beta_{\mathrm{k}_1}+\beta_{\mathrm{k}_2}+\beta_m}{(-\beta_p)^2}\right)^2 w_{pp} \qquad (11)$$

where β_{k_1}, β_{k_2} are the estimated parameters of the specific attributes and β_m is the coefficient for the interaction term, which is either β_8, β_9 or β_{10} in equations (7) and (8). $w_{\mathrm{k}_1\mathrm{k}_1}$, $w_{\mathrm{k}_2\mathrm{k}_2}$, w_{pp} and w_{mm} are the variances and $w_{\mathrm{k}_1\mathrm{k}_2}$, $w_{p\mathrm{k}_1}$, $w_{p\mathrm{k}_2}$ and w_{pm} are the covariances for the respective estimated parameters. The variance of the WTP of each attribute is calculated to determine whether the WTP is significant.

To further verify the results, WTP estimates and associated confidence intervals were also calculated using the Krinsky and Robb bootstrapping parametric method (Krinsky and Robb, 1986). Krinsky and Robb's method created the confidence interval of WTP estimates by using means and covariance matrix of the coefficient estimates. The equation to calculate the new parameter estimate is as follows:

$$b = \hat{\beta} + C'Z \qquad (12)$$

where $\hat{\beta}$ is the coefficient estimate, C' is the Cholesky decomposition of the variance-covariance matrix of $\hat{\beta}$, such that $C * C' = V_{\hat{\beta}}$ and Z is the random draw from the standard normal distribution with mean 0 and variance 1. Hence, the new vector b will follow the multivariate normal distribution with means $\hat{\beta}$ and the variance $V_{\hat{\beta}}$. By taking 1000 draws of Z, we can obtain the confidence interval of b and then calculate the WTP.

2.4. Empirical Results

2.4.1. Sample Characteristics

Participants for the Qualtrics online survey were recruited from Beijing, Shanghai and Guangzhou. Respondents had to consent to participate in the survey and only beef eaters who were at least 18 years old were surveyed. Table 2.2 presents the summary statistics for the characteristics of the full sample. Forty-seven percent of the respondents were male and 53% were female. Ten percent of respondents were in the age category 18-24 years, 34% in the category 25-34 years, 32% in the category 35-44 years, 11% in the category 45-54 years, and 10% of respondents indicated being older than 55 years. Thirty-seven percent of the respondents lived in Beijing, 41% in Shanghai and 21% in Guangzhou. About 17% of the sample had an income of less than ¥15,000 per month, 31% of ¥15,000 -¥21,000, 26% of ¥21,000 -¥25,000, and 24% had an income of more than ¥25,000 per month. Roughly 79% of the respondents had at least a bachelor's degree, which is higher than the Chinese average. Also, respondents were younger compared to the population (census data). However, this is consistent with Lin et al. (2020) whose sample was also highly educated with 85% of respondents having at least a bachelor's degree and younger respondents being moderately over-represented. This high percentage of educated and younger consumers can be partially explained with the fact that participants had to have a computer and internet access to take the survey, and younger respondents might be more willing to participate in an online survey.

Table 2.2. Sample Characteristics

Variable	Sample Percentage	China census data [a] (City)	Variable	Percentage	China census data
Gender			Education level [c]		
Male	46.61%	50.73%	Below Bachelor	20.89%	73.92%
Female	52.86%	49.27%	Bachelor degree	68.58%	20.32%
Other	0.01%		Master degree and higher	10.54%	5.75%
Age			Household income		
18-24y	10.18%	12.33%[b]	Less than ¥15k	17.20%	
25-34y	34.46%	18.16%	¥15k - ¥21k	31.90%	
35-44y	32.68%	15.71%	¥21k - ¥25k	26.52%	
45-54y	11.79%	15.98%	Above ¥25k	24.37%	
55-64y	9.64%	11.36%	City		
65 and older	1.25%	10.78%	Beijing	37.68%	
			Shanghai	41.07%	
			Guangzhou	21.25%	

[a] Source: China Statistical Yearbook (2021).
[b] This is the percentage for 15-24 years old.
[c] The percentage for education level is only counting the population from Beijing and Shanghai.

2.4.2. Chinese Consumer Preferences for Beef

Table 2.3 reports the estimated parameters for the RPL, RPL-EC, EC-PRE, and EC-REG models, respectively. Four observations had to be excluded from the data set due to missing values in the choice experiment leaving a total of 556 valid responses. As expected, the AIC had the lowest value and the highest simulated log-likelihood in the RPL-EC compared to the RPL model which indicates that the RPL-EC performed better than the RPL model. Also, the standard deviation of the additional error component term ($\mathrm{I}_j\eta_{ij}$) in the RPL-EC, EC-PRE, EC-REG models was statistically significant (p <0.01), which indicates that it was important to account for this error structure. Therefore, only results from the RPL-EC, the EC-PRE and the EC-REG models will be discussed.

As expected, the price coefficient is significant and negative (*p*<0.01), indicating that as the price of beef flank increases, consumers are less likely to purchase it. The coefficient for the none-of-these option is also negative and statistically significant (*p*<0.01), which indicates consumers obtain higher utility from selecting beef flank compared to not choosing beef flank. The significant and negative coefficients for all COOL coefficients (*p*<0.01) indicate consumers are less likely to choose beef flank from foreign countries compared to beef produced in China.

Respondents preferred beef flank carrying the Premium quality grade compared to ungraded beef flank. However, the coefficient estimate for the Regular quality grade is significant and negative (*p*<0.01), indicating that consumers have negative utility for Regular graded beef flank compared to ungraded beef flank. The larger standard deviations for Premium quality in all models compared to Regular quality indicate a greater heterogeneity in preferences for the Premium quality grade compared to the Regular quality grade. Consumers prefer Organic and Green Food beef flank compared to beef flank without this information. Notably, consumers prefer the Green Food label more than the Organic label, even though the Organic label follows more stringent production methods.

All standard deviation coefficients were significant indicating that consumers had heterogeneous preferences for all attribute levels.

In the EC-PRE model, the interaction coefficient between Brazil and Premium was significant and positive (p<0.10). This indicates that consumer utility increased for Brazilian beef of superior quality. All other interactions between COOL and quality grades were not significant. However, the standard deviations for all interaction terms in both EC-

PRE and EC-REG models were all significant (p<0.05) indicating preference heterogeneity for foreign beef with quality grade information.

Table 2.3. Results from RPL and RPL-EC Model

	RPL	RPL-EC	EC-PRE	EC-REG
Price	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Brazil	-0.98***	-1.06***	-1.11***	-1.08***
	(0.06)	(0.08)	(0.10)	(0.09)
US	-0.97***	-1.09***	-1.15***	-1.09***
	(0.07)	(0.10)	(0.11)	(0.10)
Australia	-0.57***	-0.68***	-0.69***	-0.70***
	(0.07)	(0.10)	(0.11)	(0.10)
Premium quality	0.79***	0.83***	0.76***	0.85***
	(0.07)	(0.08)	(0.10)	(0.08)
Regular quality	-0.31***	-0.35***	-0.36***	-0.38***
	(0.05)	(0.06)	(0.06)	(0.09)
Organic label	0.43***	0.49***	0.49***	0.48***
	(0.05)	(0.06)	(0.06)	(0.06)
Green Food label	0.52***	0.61***	0.63***	0.63***
	(0.05)	(0.06)	(0.06)	(0.06)
None-of-these	-5.08***	-5.92***	-5.48***	-5.47***
	(0.29)	(0.45)	(0.34)	(0.35)
Brazil*Premium			0.19*	
			(0.10)	
Australia*Premium			0.01	
			(0.11)	
US*Premium			0.12	
			(0.11)	
Brazil*Regular				0.04
				(0.13)
Australia*Regular				0.04
				(0.12)

US*Regular				0.02
				(0.12)
Standard deviations of parameter distributions				
Brazil	0.86***	1.54***	1.61***	1.59***
	(0.07)	(0.09)	(0.11)	(0.10)
US	0.94***	1.77***	1.85***	1.73***
	(0.08)	(0.11)	(0.13)	(0.11)
Australia	0.90***	1.66***	1.78***	1.64***
	(0.09)	(0.11)	(0.12)	(0.12)
Premium quality	0.76***	1.03***	0.92***	1.09***
	(0.07)	(0.17)	(0.17)	(0.17)
Regular quality	0.54***	0.53***	0.60***	0.58***
	(0.08)	(0.18)	(0.09)	(0.14)
Organic label	0.45***	0.77***	0.81***	0.79***
	(0.06)	(0.14)	(0.15)	(0.10)
Green Food label	0.40***	0.64***	0.67***	0.68***
	(0.07)	(0.10)	(0.11)	(0.09)
Brazil*Premium			0.38***	
			(0.13)	
Australia*Premium			1.15***	
			(0.19)	
US*Premium			0.64***	
			(0.16)	
Brazil*Regular				0.32**
				(0.15)
Australia*Regular				0.49***
				(0.15)
US*Regular				0.45**
				(0.19)
Error-component		3.65***	2.95***	3.04***
		(0.33)	(0.26)	(0.24)
None-of-these	2.57***			
	(0.19)			

N	6,672	6,672	6672	6672
LL	-7,128.26	-6,837.01	-6811.81	-6827.95
AIC	14,290.5	13764.0	13779.6	13811.9

Note: ***, **, * indicate significance at 1%, 5%, 10% level, respectively. Standard Errors in parentheses.

2.4.3. Chinese Consumer WTP for Beef

Chinese consumer WTP estimates from the EC-PRE and EC-REG models are presented in Table 2.4. The significance of the WTP estimates was calculated following Syrengelas et al. (2018) and Krinsky and Robb (1986). Results from both methods were essentially identical.

As depicted in Table 2.4, Chinese consumers favored domestic beef compared to beef from Australia, Brazil or the US. US and Brazilian beef were least preferred at around -¥130/kg, or $-9.21/lb ($p$<0.01), compared to domestic beef. Australian beef is the least discounted foreign beef at -¥80/kg or $-5.66/lb ($p$<0.01). Chinese consumers were willing to pay 90 Yuan (¥)/kg, or roughly $6.20/lb, more for Premium quality grade beef flank compared to ungraded beef flank (p<0.01). Compared to ungraded beef flank, consumers discounted Regular quality grade beef flank by ¥-42/kg, or $-2.94/lb ($p$<0.01). Consumers would pay ¥57/kg ($4.01lb) and ¥73/kg ($5.17lb) more for Organic and Green Food labeled beef flank, respectively (p<0.01).

Table 2.4 also shows the WTP estimates and standard errors for the interaction terms between the COOLs and quality grades. The WTP estimates for the interaction terms between COOL and quality grades generate an estimation of how beef quality affects Chinese consumer preferences for foreign beef. Results show that the WTP for foreign beef graded as Regular quality is much lower compared to beef only labeled for COOL ranging from around -¥170/kg for Brazil and US beef to -¥123/kg for Australian beef (p<0.01). On the other hand, foreign beef carrying the Premium quality grade would have the potential to increase foreign beef demand. For example, consumers in China would discount US beef if it was graded as Premium by only -¥31/kg (p<0.10), an increase of nearly ¥100/kg compared to when it does not contain quality information. While still being slightly discounted, this result indicates that consumers prefer foreign beef more if it is of superior quality.

Table 2.4. Mean WTP Estimates for Each Attribute

	EC-PRE		EC-REG	
	In ¥ /kg	In $/ lb	In ¥ /kg	In $/ lb
Brazil	-127.30***	-9.02	-126.90***	-8.99
	(14.74)		(14.37)	
Australia	-79.89***	-5.66	-82.83***	-5.87
	(15.15)		(14.68)	
US	-132.43***	-9.39	-128.91***	-9.15
	(16.12)		(15.59)	
Premium quality	87.49***	6.20	100.70***	7.14
	(14.60)		(13.06)	
Regular quality	-41.52***	-2.94	-45.19***	-3.20
	(8.21)		(11.95)	
Organic label	56.52***	4.01	57.06***	4.04
	(8.67)		(8.85)	
Green Food label	72.97***	5.17	73.82***	5.23
	(9.02)		(9.30)	
Brazil*Premium	-18.53	-1.31		
	(15.01)			
Australia*Premium	-8.97	-0.64		
	(20.82)			
US*Premium	-31.19*	-2.21		
	(19.28)			

Brazil*Regular	-167.64***	-11.88
	(10.13)	
Australia*Regular	-123.07***	-8.72
	(6.89)	
US*Regular	-171.86***	-12.18
	(9.20)	

Note: ***, **, * indicate significance at 1%, 5%, 10% level, respectively. All WTP estimates were converted from Yuan/1.15 kg to Yuan/kg. The exchange rate at the time of this study was 1 US dollar = 6.40 RMB (¥). 1 lb=0.4536 kg. Standard Errors in parentheses.

2.4.4. Chinese Consumer WTP for Beef across Cities

Tables 2.5 and 2.6 show WTP estimates based on the EC-PRE and EC-REG models by city. The direction of all WTP estimates and associated significance levels are consistent with the full sample results. However, the magnitude of WTP estimates vary by city. Consumers in Guangzhou discounted US beef the least at -¥93/kg and consumers in Beijing discounted it the most at -¥188/kg (Table 2.5). Brazilian beef was discounted the least in Shanghai at -¥120/kg and discounted the most in Beijing at -¥162/kg (Table 2.5). Australian beef was discounted the least in Shanghai at -¥55/kg and consumers in Beijing discounted it the most at -¥125/kg (Table 2.5). Compared to consumers from Beijing and Shanghai, respondents from Guangzhou discounted US beef the least and were willing to pay the most for beef flank graded as Premium. Australian beef was less discounted in Shanghai and Guangzhou compared to Beijing. In general, Beijing consumers were more opposed to imported beef compared to shoppers from Shanghai and Guangzhou. WTP estimates for the quality grades, as well as Organic and Green Food labels, were mostly consistent across cities. The most variation in WTP estimates across cities occurred for imported beef, especially for Australian and US beef.

With respect to imported beef with quality information, it was found that Brazilian and US beef were much less discounted by consumers in Beijing and Shanghai if it also carried a Premium quality grade (Table 2.5). In Guangzhou, if Australian beef was labeled as Premium, it was actually preferred compared to domestic beef (p<0.10). Meanwhile, WTP estimates for Regular quality imported beef were consistently negative across all cities (Table 2.6), with Beijing consumers having the most negative WTP for imported Regular quality beef from Australia and the US relative to the other cities.

Table 2.5. Mean WTP Estimates of EC-PRE Model for Each Attribute by City

	Beijing		**Shanghai**		**Guangzhou**	
	In ¥ /kg	In $/ lb	In ¥ /kg	In $/ lb	In ¥ /kg	In $/ lb
Brazil	-161.70***	-11.46	-120.02***	-8.51	-128.56***	-9.11
Australia	-125.11***	-8.87	-54.64**	-3.87	-74.81***	-5.30
US	-188.28***	-13.34	-117.76***	-8.34	-92.91***	-6.58
Premium quality	82.42***	5.84	89.38***	6.33	97.02***	6.88
Regular quality	-31.46***	-2.23	-50.39***	-3.57	-38.63***	-2.74
Organic label	58.68***	4.16	65.04***	4.61	49.95***	3.54
Green Food label	72.91***	5.17	86.47***	6.13	67.88***	4.81
Brazil*Premium	-50.66**	-3.59	-21.54**	-1.53	2.50	0.18
Australia*Premium	-42.91	-3.04	27.17	1.93	48.58*	3.44
US*Premium	-75.50**	-5.35	-31.94***	-2.26	18.88	1.34

Note: ***, **, * indicate significance at 1%, 5%, 10% level, respectively. All WTP estimates were converted from Yuan/1.15 kg to Yuan/kg. The exchange rate at the time of this study was 1 US dollar = 6.40 RMB (¥). 1 lb=0.4536 kg. Standard Errors in parentheses.

Table 2.6. Mean WTP estimates of EC-REG model for each attribute by city

	Beijing		Shanghai		Guangzhou	
	In ¥ /kg	In $/ lb	In ¥ /kg	In $/ lb	In ¥ /kg	In $/ lb
Brazil	-162.35***	-11.51	-122.81***	-8.70	-98.24***	-6.96
Australia	-128.71***	-9.12	-53.87**	-3.82	-55.55**	-3.94
US	-173.25***	-12.28	-126.45***	-8.96	-78.06***	-5.53
Premium quality	98.34***	6.97	96.89***	6.87	112.07***	7.94
Regular quality	-47.68***	-3.38	-48.01**	-3.40	-35.75**	-2.53
Organic label	54.41***	3.86	70.68***	5.01	43.79***	3.10
Green Food label	72.84***	5.16	88.55***	6.28	60.35***	4.28
Brazil*Regular	-168.64***	-11.95	-178.09***	-12.62	-175.96***	-12.47
Australia*Regular	-150.78***	-10.69	-114.88***	-8.14	-102.72***	-7.28
US*Regular	-230.37***	-16.33	-166.40***	-11.79	-128.54***	-9.11

Note: ***, **, * indicate significance at 1%, 5%, 10% level, respectively. All WTP estimates were converted from Yuan/1.15 kg to Yuan/kg. The exchange rate at the time of this study was 1 US dollar = 6.40 RMB (¥). 1 lb=0.4536 kg. Standard Errors in parentheses.

2.5. Discussion and Conclusion

2.5.1. Discussion of Results

Since 2017, Chinese beef consumption has been steadily increasing along with beef imports. As incomes in China rise, Chinese consumers are preferring higher quality food. Therefore, the Chinese Ministry of Agriculture and Rural Affairs recently updated the beef quality grade program. The goal of this research was to evaluate this updated policy and determine its implications. Therefore, we conducted a choice experiment in three major Chinese cities to evaluate preferences and WTP for imported beef displaying the quality grades, and to analyze how the quality grades impact the demand for beef from major exporting countries.

Consumers from Beijing, Shanghai and Guangzhou were willing to pay an extra ¥80/kg to ¥100/kg for beef flank carrying a Premium quality grade compared to ungraded beef. However, consumers in these cities discounted Regular graded beef by -¥30/kg to -¥50/kg compared to ungraded beef. This indicates that while consumers will pay a premium for beef quality, they discount beef that was labeled as Regular compared to ungraded beef. This could have large implications for Chinese beef depending on what percentage of beef flank is expected to be graded Regular versus Premium. For example, in the US, less than 10% of all graded beef qualifies as Prime, which is the highest quality label, and around 74% of all graded beef qualifies as Choice, which is the second highest quality label (USDA Agricultural Marketing Service, 2022). If a large percentage of

Chinese cattle do not qualify as Premium, this grading scheme could be problematic given Regular beef is discounted. Previous research has found that WTP estimates for US pork vary depending on how many quality grade labels are on the market and depending on the quality grade names (Lusk et al., 2018). Thus, Chinese consumer preferences for beef quality grades would likely be affected by the number of categories of grades available for beef flank. Furthermore, it is likely that the names “Regular” and “Premium” affect consumer preferences as well, given Lusk et al. (2018) found that WTP estimates differed between a quality grade scheme of “Good, Better, Best” compared to “Select, Choice, Prime”.

In 2017, the Chinese government reopened their markets to US beef imports following a BSE-related ban that began in 2003 (Reuters, 2020). Therefore, we evaluated the effect of this policy by estimating consumer preferences for foreign beef, including beef from the US. Compared to domestic beef, Chinese consumers discounted US and Brazilian beef by about -¥130/kg. Meanwhile, Australian beef was only discounted by about -¥80/kg compared to domestic beef. In general, Beijing consumers discounted foreign beef compared to domestic beef. Our results indicate Chinese consumers prefer Australian beef compared to beef from Brazil or the US, and they value US beef similar to Brazilian beef. With respect to Australia and the US, our results are counter to findings by Lin et al. (2020) and Ortega et al. (2016) who found Chinese consumers prefer Australian beef over domestic beef and do not discount US beef compared to domestic beef. The downward shift in public sentiment towards Australia and the US may have caused a decline in WTP for Australian and US beef. Fang et al. (2022) found that the perception of Chinese consumers towards the US deteriorated in 2020, and they also discovered that young and more educated respondents held more negative views towards the US. At the same time, Hu (2021) conducted a survey with 2,067 respondents in China in June 2021 asking respondents to rate their feelings towards selected countries with any number from zero to 100. They found Australia's score fell from 65.28 in 2020 to 55.61 in 2021 (Hu, 2021).

When foreign beef was carrying quality grades, WTP estimates were more favorable if the foreign beef was of superior quality (graded Premium). However, WTP estimates were more negative for imported beef if it was of lesser quality (graded Regular). For example, Chinese consumer WTP for Premium quality US beef was only -¥31/kg, an increase in WTP of almost ¥100/kg for beef that did not have quality information. In Guangzhou, Australian beef was preferred over domestic beef if it was of Premium quality. Furthermore, consumers in Beijing and Shanghai discounted US and Brazilian beef less if it was Premium quality. These results have valuable implications for beef exporters. While the specific beef quality grade is traditionally determined at slaughter by each country's respective quality grades (Texas A&M, 2022), these results show that it would be valuable to include this quality grade label on packaging abroad if it denotes superior quality. However, if the beef is not of superior quality (e.g., a grade similar to Regular), it would be advisable to not include such quality grade information on the package.

Finally, our results suggest that Chinese beef consumers were willing to pay an extra ¥ 57/kg and ¥ 73/kg for beef flank carrying Organic and Green Food labels, respectively, compared to beef flank without such information. While Organic certification is more stringent, it received a lower premium than the Green Food label. This result is consistent with Ortega et al. (2016) who found consumers were willing to pay a higher premium for the Green Food label compared to the Organic label.

2.5.2. Policy Implications

This study contributes to the literature on quality grade systems in China by examining Chinese consumer preferences for the updated Chinese beef quality grade system and how quality grades impact consumer preferences for imported beef. The associated policy implications suggest that heavy discounts are placed on Regular graded beef while Premium graded beef can result in large premiums. Thus, this grading system would achieve China's desired goal of creating incentives for Chinese cattle producers to produce higher quality beef. However, it should be estimated how much Chinese beef would qualify as Premium versus Regular so price discounts do not result for the majority of beef produced. Findings showed that Chinese consumer demand for beef from major exporting countries, such as, Australia and the U.S. decreased compared to previous findings. One possible explanation could be that the downward shift in public sentiment towards both countries led to a decrease in WTP for Australian and US beef. Moreover, we also found a difference in preferences for imported beef across cities, where Australian beef was discounted least in Shanghai while US beef was discounted least in Guangzhou. Companies focusing on exporting Australian beef to China should first consider expanding their markets in Shanghai compared to the other two cities. In contrast, US beef exporters could benefit more by targeting the beef market in Guangzhou first. Our results also showed that Chinese consumer preferences for foreign beef could be improved if it contained a label distinguishing it as being of premium quality. Thus, countries exporting beef to China might benefit from labeling their premium quality beef as such. However, major beef exporting countries should avoid being assessed as regular quality given that our results indicate that Chinese consumers value imported beef carrying a regular quality grade the lowest.

2.5.3. Future Research

Overall, this study specifically examines preferences of Chinese consumers for beef with varying quality grades, and how quality grading impacts demand for imported beef. While we examined beef flank in three major cities in China, future studies using other beef products, such as steak, and surveying consumers from other regions will be helpful in further analyzing consumer preferences for Chinese beef quality grades and the effects of quality grades on imported beef demand. Given our study found discounted WTP for imported beef, it will be fruitful to further study underlying reasons for this. For example, by analyzing consumers' perceptions and their attitudes toward beef from major importing countries. Moreover, although we aimed to reduce hypothetical bias by using shelf-simulation and a cheap talk script, our results may still be subject to hypothetical bias. Future research could estimate consumers' WTP for beef with quality grades using other experimental methods, such as, non-hypothetical auctions to verify the results. Furthermore, the updates to the revised Chinese beef quality grade system will soon be implemented. Thus, future research could investigate the adoption of this quality grade system in the retail market to test how it compares to other Chinese food quality and safety labels.

CHAPTER 3

CHINESE CONSUMERS'WILLINGNESS TO PAY FOR COUNTRY-OF-ORIGIN LABELED BEEF: THE ROLE OF ETHNOCENTRISM, COUNTRY IMAGE, AND PRODUCT

3.1. Introduction

The country-of-origin (COO) label is a common and widely adopted label for food products. In general, COO labels influence consumer behavior in at least two different ways (Lusk et al., 2006; Josiassen, 2011). First, COO labeling and food quality often correlate with each other in that products from certain countries may be perceived as having a better quality. Second, because of the affinity to their home country, consumers may prefer domestic food products over imported food (Shimp and Sharma, 1987, Lusk et al. 2006). Other literature divided COO effects into three components: cognitive, affective, and normative (Verlegh and Steenkamp, 1999; Ehmke et al., 2008). Based on Verlegh and Steenkamp (1999), COO labels are a cue for product quality and quality attributes with respect to the cognitive aspect. The affective aspect refers to symbolic and emotional values that COO labels evoke in consumers. Social and personal norms related to COO labels belong to the normative component (Verlegh and Steenkamp, 1999).

More specifically, the cognitive aspect represents consumers' perceptions of food quality from certain countries. Here, COO labels serve as a "cue" attribute, which conveys food quality information to consumers (Caputo et al., 2017). In this case, COO labels can affect consumers' behavior through both country and product images. Product image refers to a belief expressed through the image the product evokes or an association with the product (Xin and Seo, 2020). For example, wines from France, and hams from Spain are perceived as high-quality products (Shankarmahesh, 2006). Other examples of product image include German products being perceived as made with precision or workmanship, and Japanese cars being considered durable (Wang et al. 2012). Country image, on the other hand, refers to the mental representation of a country and its people, including both perceptions of the economic and technologic stage of a country and beliefs, e.g., regarding a country's social and political system (Wang et al. 2012). Martin and Eroglu (1993) defined country image as the sum of all descriptive, inferential and informational beliefs one has about a particular country and claimed the three underlying dimensions of country image are economic, political and technological (Martin and Eroglu, 1993). Previous literature tended to connect country image with product image. For example, Nagashima (1970, 1977) defined country image as "the total of beliefs one has about the products of a given country". However, more recent literature is more likely to differentiate country image and product image (Josiassen, 2011; Shankarmaheshm, 2006; Pappu et al., 2007). As mentioned by Wang et al. (2012), the general country image is distinct from products associated with a particular country (product image).

The affective information associated with COO labels has symbolic and cultural values for consumers, including social status and national pride (Ehmke et al., 2008; Verlegh and Steenkamp, 1999), while the effect of consumers' social norms and personal beliefs on their attitudes for COO labels have been interpreted by the normative aspect (Ehmke et al., 2008; Verlegh and Steenkamp, 1999; Shimp and Sharma, 1987). Examples include consumer ethnocentrism and patriotism, their affinities to their home country, consumers' misidentifications, and their animosities (Klein et al., 1998; Shimp and Sharma, 1987; Oberecker et al., 2008; Josiassen, 2011). In this regard, Shimp and Sharma (1987) recognized both the affective and normative elements of COO labels when they developed the Consumer Ethnocentrism Tendencies Scale (CETSCALE), an associated measurement for consumer ethnocentrism (Ehmke et al., 2008). Consumer ethnocentrism is defined as "*the beliefs held by (American) consumers about the appropriateness, indeed morality, of purchasing foreign made products*" (Shimp and Sharma, 1987).

According to Verlegh and Steenkamp (1999), cognitive, affective and normative components are constantly interacting, which means they are not independent from each other and they need to work simulaternously to determine COO effects. However, when they act together, they can operate in opposite directions. For example, a consumer can be favorable towards an imported product (affective component) but still decide to buy the domestic goods because of the belief that buying the foreign goods will hurt the domestic economy (cognitive component) (Herche, 1992; Kilders et al., 2021).

This study aims to evaluate the effects of ethnocentrism, and country and product images on consumers' preferences and willingness to pay (WTP) for COO labels of domestic and foreign beef. To do so, we will draw on data from a 2021 online consumer choice experiment for beef flank conducted in China. China was examined because it is the country with the world's largest population and, amplified by a tight pork supply due to African swine fever, Chinese beef imports have been growing for the last eight consecutive years (USDA, 2022). In 2021, Chinese beef imports accounted for more than 30% of the global beef imports (USDA, 2022). Thus, China is an important emerging beef export market.

While beef imported to China has steadily been increasing, Chinese levels of ethnocentrism and their public sentiment with regards to foreign countries likely has been changing in the past several years given recent unprecedented events (e.g., COVID-19, U.S. trade war). Research has documented the Chinese public sentiment with respect to some of the largest beef exporters to China such as the U.S. and Australia. Fang et al. (2022) conducted a survey with 2,083 Chinese adults from October 2020 to February 2021, and found younger and more educated Chinese respondents held more negative views toward the U.S. Another study conducted by Godfarb et al. (2021) reported that about 60% of Chinese respondents had an unfavorable view of the U.S. Hu (2021) asked 2,067 respondents to rate their feelings toward selected countries with any number between zero and 100, and found that the score for Australia dropped from 65.28 in 2020 to 55.61 in 2021.

Against this background, the objective of this study is two-fold. The first goal is to investigate Chinese consumer ethnocentrism, how favorable Chinese consumers perceive Australia, Brazil and the U.S. (countries that export beef to China), and their perception of the safety of beef from these countries. The second goal is to determine how these factors affect Chinese consumer preferences and WTP for beef originating from those countries. Overall, this study examines how Chinese consumer ethnocentrism, product and country images affect their preferences for beef from different countries.

3.2. Background on China’s Beef Exports

China’s beef import value has been rising since 2017 (Figure 3.1). In 2021, China’s total beef import value was $12.49 billion --four times more than the whole beef import value in 2017.

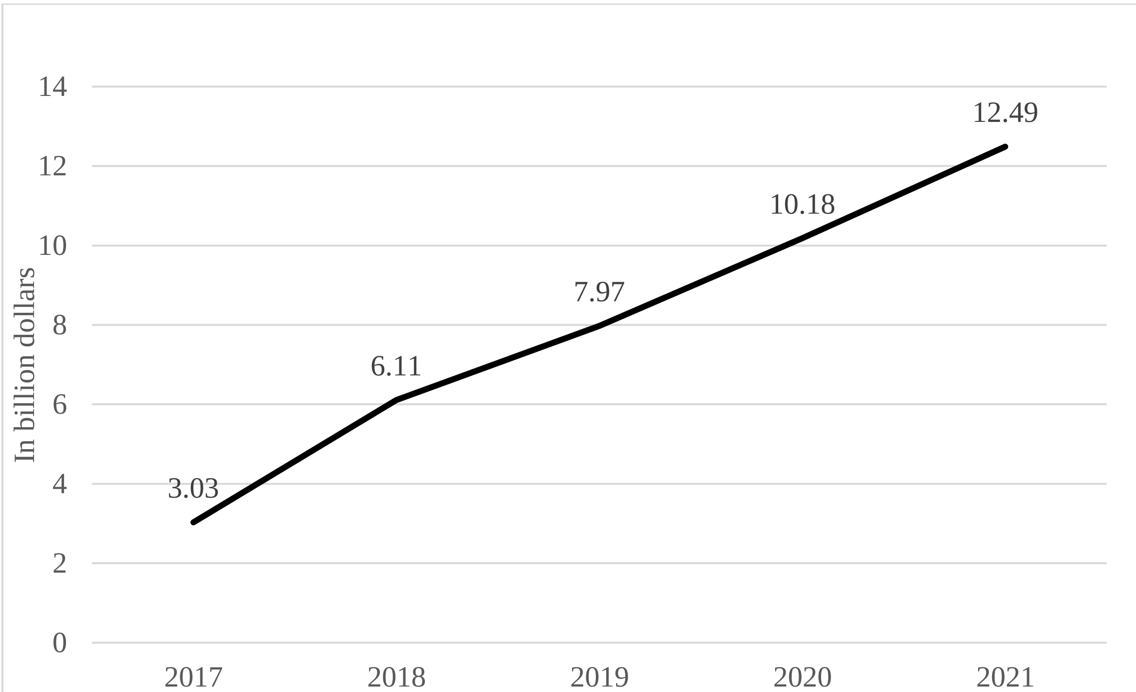


Figure 3.1. Chinese Beef Import Values from 2017 to 2021. Source: China Customs Statistics, 2022

Figure 3.2 shows the percentage of beef import values to China from major beef exporting countries between 2017 and 2021. As displayed in Figure 3.2, 95% of beef imports originate in Australia, Argentina, Brazil, the U.S., Uruguay, and New Zealand. Considering the total beef export value to China, beef imports from Australia decreased from 21% in 2017 to 9% in 2021, and imports from Uruguay decreased from 21% in 2017 to 12% in 2021. At the same time, imports from Brazil increased from 25% to over 40% in 2020. Although it decreased slightly in 2021, Brazilian beef still accounted for 37% of the value of China’s beef imports. Imports from Argentina also increased from 12% in 2017 to 20% in 2020. Furthermore, after banning the U.S. from importing beef into China due to BSE-related restrictions in 2003, China reopened to U.S. beef imports in 2017, allowing imports of deboned and boned beef from American cows under 30 months old (Reuters, 2020). Beef imports from the U.S. increased from approximately 2% in 2020 to 11% in 2021 (Figure 3.2). More specifically, the total U.S. beef export value significantly increased in the last two years by over a billion dollars. The U.S. is now the 3rd largest beef exporting country to China behind only Brazil and Argentina. Given this, we evaluate Chinese consumer preferences for beef from Australia, Brazil and the U.S., three of the major beef export countries in the Chinese beef market.

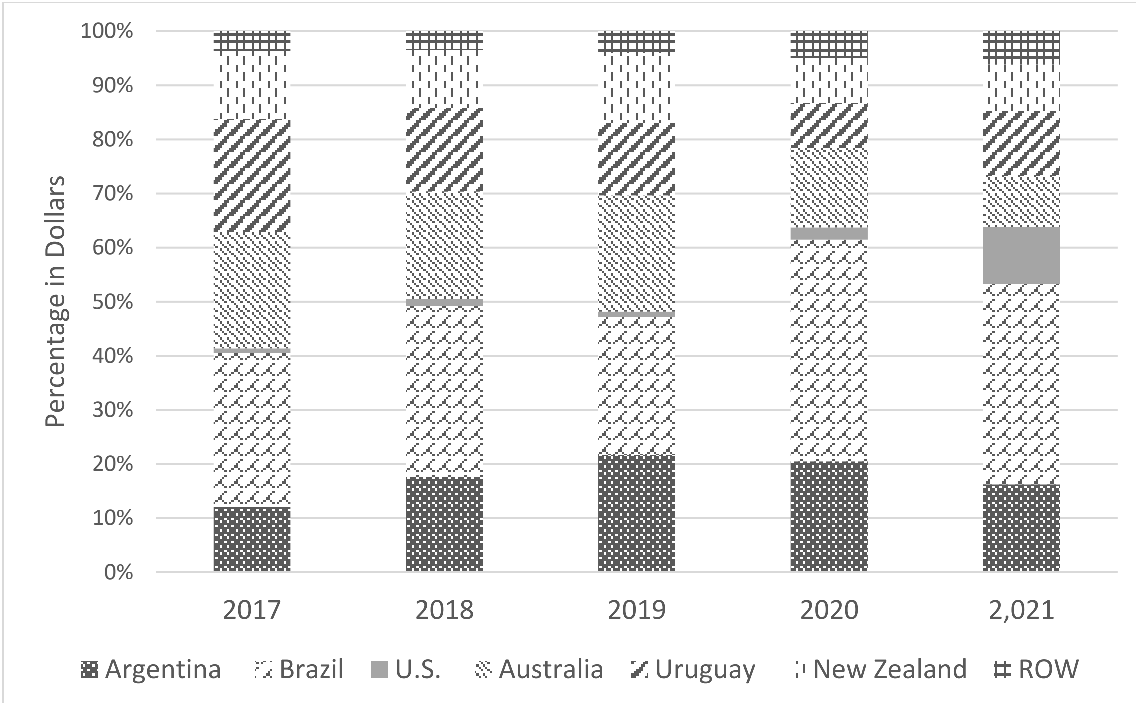


Figure 3.2. Percentage of Chinese Beef Imports Values by Countries. Source: China Customs Statistics, 2022

3.3. Literature Review

3.3.1. Country-of-Origin Labeling

Umberger (2010) argued that COO labels are perceived by consumers as an extrinsic credence attribute, and Balcombe et al. (2016) claimed the value of COO labeling is typically context-dependent in that it will depend on what other 'quality' cues are being offered to survey respondents. In fact, WTP for COO labeling does not necessarily have to be positive. As Lusk et al. (2004) found, consumers may not wish to pay a premium for COO labeling either because they do not value the information sufficiently or do not believe the information provided. Over the past few decades many studies have been conducted testing consumers' preferences and WTP for COO labeling on food products.

Focusing on meat products, Lim et al. (2013) stated that WTP for COO labeling is consistent across different types of meat, and Peschel et al. (2016) studying British and German consumers' WTP for beef, showed that COO is most likely to be chosen as a cut-off point even compared to a food standard assurance label, hormone-free label, and gourmet label. They also found that COO is the most crucial information for highly involved shoppers. Regarding beef preferences of British and German consumers, Lewis et al. (2017) found that consumers from the U.K. and Germany prefer domestic beef over foreign beef, and British shoppers like Argentinian beef the least while German consumers like British beef least. Lin et al. (2020) found that Chinese consumers are willing to pay $1.11/pound to upgrade from domestic beef or U.S. beef to Australian beef. However, there is heterogeneity in preferences toward U.S. beef, and the WTP for U.S. beef ranges from -$18 to $10 per pound.

3.3.2. Ethnocentrism

A large body of research has studied the impact of Chinese consumers' ethnocentrism on purchasing behaviors towards domestic and foreign products and brands. Ortega et al. (2017) found that consumers from China are willing to pay more for domestic pork compared to imported pork from the U.S. They also found that more patriotic consumers from China are less likely to pay more for U.S. pork. Qing et al. (2012) applied only three items from CETSCALE to analyze Chinese consumers' purchase intentions toward both domestic and imported fresh fruit, and found a positive relationship between consumers' ethnocentrism and purchase attitudes towards domestic fruit. Yin et al. (2019) used six attitudinal statements in conjunction with choice experiments to analyze the impact of ethnocentrism on WTP for organic labels and certifiers from different countries. They concluded that an increase in ethnocentrism would decrease WTP for foreign organic labels and increase WTP for the Chinese organic label. He and Wang (2015) used four items from the CETSCALE to study consumers' preferences for domestic and foreign brands, and found ethnocentrism negatively affects the preference for import brands. However, the impact disappeared on actual purchases for domestic or import brands. Han and Guo (2018) applied a 10-item CETSCALE and found consumer ethnocentrism only has a significant impact on purchases of domestic brands. Furthermore, they found that brand choices of consumers who have a greater preference for foreign brands are less affected by their ethnocentrism levels.

3.3.3. Country Image and Product Image

As mentioned above, COO labels can affect consumers' behavior through country image and product image. Previous literature has concluded the positive effect of country image on purchase intention of domestic and foreign products (Xin and Seo, 2020; Yeh et al., 2010). Zhang et al. (2020) used auction methods to analyze the effect of county image on Chinese consumers' WTP for milk carrying different COO labels, and found country image had a significant and positive effect on consumers' WTP. Yeh et al. (2010) found a significant impact of country image on purchase intention. They also concluded that the country image effect is not correlated with the economic development level of that country (Yeh et al. 2010).

Product image, which refers to the overall perceptions or beliefs consumers have towards products from a given country (Wang et al. 2012), has also been studied. Here, the previous literature focused on the effect of product image on consumers' purchase intentions (Han, 1989; Xin and Seo, 2020; Dagger and Raciti, 2011; Wang et al. 2012).

Dagger and Raciti (2011) found product image, such as innovation, has a significant impact on Australian consumers' WTP for automobiles and watches. However, this effect disappeared when measured related to WTP for beer and leather goods. Xin and Seo (2020) found product image directly influenced Chinese consumers' purchase attitudes towards Korean functional food.

Wang et al. (2012) used mediation analysis to test how both country image and product image affect consumers' purchase intention. They found that the impact of cognitive country image on purchase intention is mediated by product image and the affective country image has a direct influence on purchase intention which is independent from product image.

However, a limited amount of studies have focused on explaining the effect of ethnocentrism, country image and product image on consumers' preferences and WTP for products. As far as the authors are aware only Zhang et al. (2020) have used a BDM auction to study ethnocentrism and country image. Hence, we extend the literature by analyzing how a variation in ethnocentrism, country image and product image affect consumers' WTP for COO labels on food products.

3.4. Design of the Study

3.4.1. Experimental Design

Discrete Choice Experiments (DCEs) were used to elicit Chinese consumer WTP for beef from different countries. Estimating WTP is a common objective in the use of DCEs (Hensher et al. 2005), and they have been widely used in studying consumers' preferences and WTP for meat products globally (Yang et al., 2020; Syrengelas et al., 2018; Merritt et al., 2018; Chung et al., 2012; Peterson and Burbidge, 2012).

In our DCE respondents are asked to choose between beef flank product alternatives from four countries and one "none-of-these" alternative. This labeled choice experiment was chosen because our goal is to estimate an alternative-specific parameter for each country (Hensher et al. 2005). In this labeled choice experiment all choice tasks contain four alternatives corresponding to beef flank from each of the four countries tested plus a "none of these" alternative. The prices for each alternative vary for each choice set. The four beef flank alternatives in each choice task originate from either China, the U.S., Australia, or Brazil. The beef flank options in each choice question are also characterized by one of four price levels, which were chosen based on beef price data in 2021 from the Beijing Municipal Price Supervision Center and market observation (BMPSC, 2021). The price levels range from 56 Yuan/kg to 146 Yuan/kg in 30 Yuan increments. Given the fact that we have four price levels and four alternatives (except the "none") in each choice question, there will be 256 (4^4) possible choice tasks if we applied a full factorial design; an experimental design can include every alternative at every price level--which is too large to conduct. Hence, to create a manageable amount of choice tasks, a simultaneous orthogonal design was programmed with NGene. The simultaneous orthogonal design has the advantage that the orthogonality not only holds within each alternative, but also across alternatives (ChoiceMetrics, 2021).

The simultaneous orthogonal design resulted in 36 choice tasks, and we further reduced the number of choice questions that each respondent needed to answer using a block technique, which led to four blocks with 9 choice tasks in each block. Each respondent was randomly assigned to one out of four blocks with 9 choice questions, which was presented in random order to avoid both fatigue and ordering effects (Bradley and Daly, 1994; Savage and Waldman, 2008; Hess et al., 2012; Carlsson et al., 2012). An example of the choice task is presented in Figure 3.3. Moreover, a cheap talk script was provided to respondents before answering the choice questions to reduce hypothetical bias (Cummings and Taylor, 1999; Lusk, 2003; Tonsor and Shupp, 2011).

The data were collected through Qualtrics in three major cities in China: Beijing, Shanghai, and Guangzhou, using an online survey in summer of 2021. The three cities were chosen because of their mature retail consumer markets (Deloitte, 2010; Bin, 2021). Participants had to be at least 18 years old and eat beef to participate in the survey. In total, 560 completed surveys were collected. This research was considered exempt by the university ethics board (IRB) of (*omitted for review*) University in the U.S. The survey instrument was registered on aspredicted.org.

种类 Alternative	A	B	C	D
产地 Country of origin	中国 China	美国 U.S.	澳大利亚 Australia	巴西 Brazil
价格 Price	146 元/kg (Yuan/kg)	146 元/kg (Yuan/kg)	86 元/kg (Yuan/kg)	116 元/kg (Yuan/kg)

Figure 3.3 Example Choice Task

3.4.2. CETSCALE, Country and Product Image Survey Instruments

To elicit consumer ethnocentrism, the 10-statement CETSCALE developed by Shimp and Sharma (1987) was used. This version has been validated by numerous studies (Seitz and Roosen, 2015; Van Loo et al., 2019; Han and Guo, 2018). In our survey, all 10 items from the CETSCALE were provided in random order to avoid ordering effects (Carlsson et al., 2012). An example of a statement is "*It is not right to purchase foreign products, because it puts Chinese people out of jobs*". Statements were rated on a 7-point Likert-scale.

Country image can be measured in a number of ways. For instance, Wang et al. (2012) divided country image effects into affective and objective components. They found that the affective component of country image is independent from the product image and can directly affect consumers' purchase intention (Wang et al. 2012). Looking specifically at scales measuring affective country image, Xin and Seo (2020) used statements, such as, "Korea is good" and "Korea is reliable". Wang et al. (2012) measured affective country image using statements, such as, "USA is friendly towards us" and "USA is likable". Hence, we followed this research by measuring the affective component of country image with the question "*How favorable is your opinion of the following countries?*" The countries listed were China, the U.S., Australia and Brazil. Answers ranged from "Very unfavorable" to "Very favorable" on a 5-point Likert-scale. We followed Ning (2020) and picked "好感" as the Chinese word to translate "Favorable". This question has also been used in the Pew Research Center Global Attitudes Survey (Silver, 2021; Silver et al. 2021).

Next, we elicited product image by asking the following question: "*In your opinion, how safe is beef from the following countries?*" Again, the countries listed were China, the U.S., Australia and Brazil. The answers ranged on a 5-point Likert scale from 1= Not very safe to 5 = Very safe. We chose to focus on food safety in addition to favorableness because safety of beef is a credence product attribute that cannot be evaluated by consumers when purchasing beef (Caswell and Mojduszka, 1996), and they often use COO labeling to infer food safety (Grebitus, 2008). Previous literature has also used food safety to measure product image (Xin and Seo, 2020).[2]

To sum up, we focus on both country image and product image by using questions related to favorableness and safety in order to capture the emotional factors that affect WTP for beef originating in a certain country. The specific survey questions are provided in Appendix B.

[2] Xin and Seo (2020) used a 5-Point Likert Scale to measure food image which can be considered a product image. While they used five statements, such as, "Korean functional food has good quality" and "Korean functional food is safe", we only adopted their statement on safety in our survey.

3.5. Data Analysis

3.5.1. Random Parameters Logit Model

Consumers' preference for beef flank from different countries was modeled based on both the theory of value and the random utility theory studies of decision-making (Lancaster, 1966; McFadden, 1974). The consumer's utility of choosing beef flank from different countries is obtained based on a product's sub-utilities for its separable characteristics or attributes, such as, COO. Based on this framework, the utility function for individual *i* choosing beef flank alterative *j* in choice question *t* is:

$$U_{ijt} = \mathrm{V_{ijt}} + \epsilon_{ijt} \tag{2}$$

where ϵ_{ijt} is the unobserved or random part of the utility function and $\mathrm{V_{ijt}}$ is the systematic component of the utility function, which depends on alterative *j* in choice question *t*. $\mathrm{V_{ijt}}$ is defined as:

$$V_{ijt} = \mathrm{ASC}_j + \beta_p * Price_{ij} \tag{3}$$

where ASC_j is the alternative-specific constant (ASC), representing the difference between the utility from choosing alternative *j* and the utility of choosing the none-of-these option, which is normalized to zero for identification. More specifically, the ASC_j in our model represents beef from China, Australia, the U.S., or Brazil. β_p is the marginal utility of the price, and $Price_{ij}$ is the price level of alternative *j* that respondent *i* faced. After combining equation (2) and equation (3), the ultimate utility function we estimated is specified as follows:

$$U_{ijt} = \beta_1 Chi_{\mathrm{jt}} + \beta_2 USA_{\mathrm{jt}} + \beta_3 Aus_{\mathrm{jt}} + \beta_4 Brz_{\mathrm{jt}} + \beta_p * \mathrm{Price}_{ij} + \epsilon_{ijt} \quad (4)$$

where *Chi, USA, Aus, Brz* are four dummy variables, indicating whether the beef flank originated in China, the U.S., Australia, or Brazil. Therefore, all COO are compared to the none-of-these option. β_{1-4} are ASCs and assumed to be random variables, following a normal distribution. β_p is assumed to be fixed in order to estimate the distribution of consumers' WTP for COO (Train and Weeks, 2005). By assuming that ϵ_{ijt} follows the Type I Extreme Value distribution, the unconditional probability of individual *i* choosing beef flank alterative *j* is:

$$P_{ij} = \int \prod_{t=1}^{T} \frac{e^{V_{ijt}}}{\sum_j e^{V_{ijt}}} f(\beta_{1-4} \mid \Omega)\, d\beta_{1-4} \quad (5)$$

Equation (5) was estimated by applying simulated maximum likelihood estimation and using 500 Halton draws for the simulation part in NLogit 6.0. Similar to Grebitus and Van Loo (2022), we use this to calculate the individual WTP for each respondent, such that $WTP_i = \beta_{ij}/{-\beta_{pi}}$, where β_{pi} is the "individual-specific" marginal utility of price and β_{ij} is the "individual-specific" marginal utility obtained from choosing beef flank from each country The individual WTP represents their WTP for beef from each country compared to not choosing beef from China, the U.S. and Brazil. The individual WTP serves as the dependent variable in the subsequent analysis of the effect of ethnocentrism, product and country images on WTP for COO.

3.5.2. Linear Regression

We estimated the effect of consumer ethnocentrism levels, country image and product image on individual consumer WTP for beef from each respective country compared to not choosing any beef (e.g., the “none of these” option) using a linear regression with robust standard errors. Following Train (2009), the estimated coefficients from the above described RPL model can be used to calculate ‘individual-specific’ marginal WTP for each respondent, and these marginal WTP values can serve as the dependent variable in the linear regression to study how they vary by socio-economic and attitudinal characteristics, such as, ethnocentrism levels, country and product images. This two-step procedure has been used in the literature, for instance, by Caputo (2020), Grebitus and Van Loo (2022), and Van Loo et al. (2020).

In our study, we estimated seven linear regression models separately to explore the effects of ethnocentrism, country and product images on WTP for COO.

$$WTP\_COO_{ic} = \beta_0 + \beta_1 \text{Limited Imports Factor} + \beta_2 \text{Buy Chinese Factor} + \beta_3 \mathrm{CI}_{ic} + \beta_4 \mathrm{PI}_{ic} + \epsilon_i \quad (6)$$

where WTP_COO_{ic} in equation (6) represents the individual-specific WTP for choosing beef flank from a given country compared to not choosing beef from China, the U.S. and Brazil (e.g., the “none of these” option in the choice set). Since we included China, the U.S., Australia and Brazil, we estimated equation (6) for each country, respectivately. β_1 and β_2 are the coefficients for two factors obtained from factor analysis related to consumers’ ethnocentrism level. β_3 is the country image coefficient associated with a specific country, which is elicted from the country image question. For example, in the model where we estimated equation (6) for Chinese beef, β_3 serves as the coefficient of the country image score of China. It changes to the coefficient for the county image score of Brazil in the model where WTP_COO_{ic} represents the WTP for Brazilian beef. Similarly,

β_4 is the product image coefficient associated with a particular country, which is elicted from the product image question. We model both product image and country image simulatenously given Wang et al. (2012) has shown the affective country image can affect consumers' purchase intention directly and is independent from the product image. We also use the *coldiag2* command in Stata to check the multiconiearity (Belsley 1991).

3.6. Results

3.6.1. Sample Characteristics

Table 3.1 shows the socio-demographic characteristics of the full sample. Fifty-three percent of the respondents were female and 47% were male. In terms of age and education level, roughly 67% of all respondents in our sample were in the category 25-44 years and had a bachelor's degree. About 30% of the full sample earned ¥15,000 -¥21,000 per month for their households. With regards to the location of the sample, 37% of the respondents were from Beijing, 41% of respondents were from Shanghai, and 21% lived in Guangzhou. Overall, our sample contained more highly educated respondents, and female, younger respondents are moderately over-represented compared to the Beijing census data. However, this is consistent with Ortega et al. (2022) whose sample was also highly educated with 86% of respondents receiving some university education, and female and younger respondents being slightly over-represented. The threshold to participate in the online survey included having internet access and being familiar with the whole process from recruiting to answer questions on their computers or phones. This may cause the sample to over-represent younger and well-educated people.

Table 3.1. Socio-Demographic Characteristics (%)

Variable	Sample (N=560)	Census[a]	Variable	Sample (N=560)	Census
Gender			Education level [c]		
Male	46.77	51.14	Below Bachelor	20.89	52.38
Female	53.05	48.86	Bachelor degree	68.58	39.89
Other	0.18		Master degree and higher	10.54	7.72
Age			Household income (Monthly)		
18-24y	10.18	9.06[b]	Less than ¥15k	17.20	
25-34y	34.46	20.13	¥15k - ¥21k	31.90	
35-44y	32.68	17.11	¥21k - ¥25k	26.52	
45-54y	11.79	14.79	Above ¥25k	24.37	
55-64y	9.64	13.77	City		
65 and older	1.25	13.30	Beijing	37.68	
			Shanghai	41.07	
			Guangzhou	21.25	

[a] Source: Beijing Statistical Yearbook (2021).

[b] This is the percentage for 15-24 years old.

[c] The percentage for education level is the percentage of citizens from Beijing who are over 15 years old.

3.6.2. Ethnocentrism

Table 3.2 presents summary statistics of consumers' ethnocentrism measured by the CETSCALE. The mean of each statement ranges from 3.37 to 5.05, and the overall mean score of all 10-item CETSCALE is 3.99 with the standard deviation equal to 1.34. More specifically, consumers are more likely to agree with statements related to "supporting Chinese products". On the other hand, statements related to "against buying foreign products" are more likely to be disliked by respondents than other statements.

Next, principal component factor analysis was applied to reduce the number of statements into uncorrelated factors. We used the Kaiser-Meyer-Olkin (KMO) criterion to test the validation of the CETSCALE. The overall KMO was 0.9327, which is considered to be marvelous (Kaiser, 1974). In order to reduce potential multicollinearity, factors were retained with eigenvalues greater than one using orthogonal varimax rotation, which maximizes the variance of the squared loadings within factors (Kaiser, 1958). The principal component factor analysis generated a two-factor solution, which explains 69.93% of the total variance of consumers' ethnocentrism attitudes. This result is consistent with Kilders et al. (2021), who used 17 items of the CETSCALE and found that 57.6% of total variance could be explained by four factors. The two-factor solution is in line with Lewis and Grebitus (2016), who studied U.S. consumers' ethnocentrism and also obtained two factors. The factor loadings are also presented in Table 3.2.

The first factor contains seven CETSCALE statements, which is associated with purchasing behavior toward foreign goods and the consequences on China because of foreign product purchasing. The perception of purchasing foreign products is an important part of consumers' ethnocentrism (Shimp and Sharma, 1987). This factor is called "Limited Imports Factor" and is hypothesized to have a negative effect on WTP for imported beef flank. Factor 2 includes the last three statements and mainly focuses on buying Chinese products. Factor 2 is called "Buy Chinese Factor" and is hypothesized to positively affect consumers' WTP for Chinese beef flank.

Table 3.2. CETSCALE Summary Statistics and Rotated Factor Loadings

Statement	Mean	S.D.	Factor 1	Factor 2
Only those products that are unavailable in China should be imported.	3.65	1.87	0.78	
Purchasing foreign-made products is un-Chinese.	3.42	1.89	0.87	
It is not right to purchase foreign products, because it puts Chinese people out of jobs.	3.37	1.85	0.88	
Chinese people should not buy foreign products, because this hurts Chinese business and causes unemployment.	3.40	1.83	0.85	
We should purchase products manufactured in China instead of letting other countries get rich off us.	4.04	1.74	0.60	
We should buy from foreign countries only those products that we cannot obtain within our own country.	3.74	1.83	0.73	
Chinese consumers who purchase products made in other countries are responsible for putting their fellow Chinese people out of work	3.62	1.79	0.79	
Chinese products first, last and foremost.	5.05	1.60		0.79
Real Chinese people should always buy Chinese-made products.	4.55	1.77		0.71
It may cost me in the long run but I prefer to support Chinese products.	5.03	1.60		0.84
Average (for all 10 items)	3.99	1.34		
Explained variance			0.46	0.24

Note: Missing values were replaced with the mean of each statement.

3.6.3 Country Image and Product Image

Table 3.3 presents the summary statistics of Chinese consumers' attitudes toward different countries and their perceptions of beef from different countries as per our country and product image survey questions (measured on a 5-point Likert scale). Not surprisingly, consumers are in favor of China with the mean equal to 4.45. With regards to importing countries, results show consumers have the most favorable opinion towards Brazil before Australia and the U.S., with the average favorable score equaling 3.53. The country image for Australia is slightly lesser than for Brazil, and respondents have a neutral opinion towards the U.S. with an average score of 3.07. However, the highest standard deviation for the U.S. indicates respondents have the most heterogeneous country image towards the U.S. than other countries. Regarding the product image, Chinese consumers perceive beef from China as safest, and they believe Australian beef compared to beef from Brazil or the U.S. is safer. Specifically, they have the similar perception on safety of U.S. beef and Brazilian beef.

Table 3.3. Summary Statistics for Country Image and Product Image (N=560)

	Mean	S.D.
Country Image		
China	4.45	0.90
Brazil	3.53	0.93
Australia	3.44	1.09
U.S.	3.07	1.16
Product Image (Beef Safety)		
Chinese Beef	4.29	0.85
Australian Beef	3.83	0.95
Brazilian Beef	3.59	0.86
U.S. Beef	3.50	1.02

Note: Missing values were replaced with the mean of each statement. The correlation between country image and product image for Australia, Brazil and the U.S. ranges between 0.54 to 0.56, and the product image and country image correlation for China is 0.65.

3.6.4. Effect of Ethnocentrism, Country and Product Images on WTP for Domestic and Imported Beef

The choice experiment data were first analyzed using the RPL model (results are shown in in the Appendix C). Overall, the RPL results show that Chinese consumers have heterogeneous preferences for beef flanks from all countries. Regarding beef flank from different countries, consumers prefer beef flank from China most and Australian beef is the most preferred imported beef followed by U.S. beef. Brazilian beef flank is the least preferred option. We use those results to calculate WTP for beef from each country compared to the none of these option. Then we apply ordinary least square regression with robust standard errors to estimate how ethnocentrism, country and product images affect consumers' WTP for COO labels using individual WTP for each COO as the dependent variable (see Appendix D for individual WTP estimates results). The results are shown in Table 3.4.

Following Belsley (1991), our regression model is considered free of multicollinearity since the estimated Condition Indexes for all independent variables were below 30. The significant and positive coefficient for the "Buy Chinese" Factor indicates that consumers who care more about buying Chinese products have a higher WTP for Chinese beef flank compared to not choosing any beef. The coefficient of the "Buy Chinese" Factor is significant and negative in the U.S. and Australian models, which indicates consumers have a lower WTP for U.S. and Australian beef the more they agree with statements related to the Buy Chinese factor. Surprisingly, the "Limited Imports" Factor does not show a significant impact on WTP for Chinese, U.S., and Australian beef flank. It significantly and negatively affects WTP for beef flank from Brazil. On the other hand, the significant and positive coefficient for the "Buy Chinese" Factor when regressing WTP for Brazilian beef indicates that consumers with high incentives for purchasing Chinese products have a higher WTP for Brazilian beef.

All coefficients related to country image and product image, indicating their favorable attitudes towards the respective countries and their products are significant and positive, indicating the more favorable opinions consumers have toward the country and the safer they believe these countries' products are, the higher their WTP for beef from that country. Also, the magnitude for the China, Australia and Brazil country image coefficients is bigger than the magnitudes of coefficients for ethnocentrism. For example, consumers are willing to increase their WTP for Chinese beef by 41.44 Yuan and 43.43 Yuan if the unit of their favorableness levels towards the respective countries or their perceptions of safety of beef from the respective countries increases by one, respectively, which is higher than their marginal WTP after increasing their ethnocentrism level by one unit. Consumers are also willing to pay a premium of 6.11-9.30 Yuan for U.S., Australian and Brazilian beef for a one unit increase of their country image and product image measures. Moreover, the affective component of country image has a higher impact on WTP for U.S. beef than product image; and product image could increase WTP for Chinese, Australian and Brazilian beef more than country image compared to not purchasing beef from those three countries. The socio-demographic results indicate that consumers from Beijing are willing to pay more for Chinese beef compared to consumers from Shanghai or Guangzhou, and older consumers are willing to pay more for U.S. beef and have a lower WTP for Brazilian beef.

Table 3.4. Ethnocentrism, Country Image and Product Image Effects on WTP for COOL

	WTP_CHINA		WTP_U.S.		WTP_AUS		WTP_BRZ	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Limit Import Factor	10.63	7.02	2.85	2.38	0.83	2.21	-5.14***	1.65
Buy Chinese Factor	27.00***	7.18	-12.12***	2.43	-4.12*	2.14	3.28**	1.55
Country Image	41.44***	9.92	9.30***	2.59	7.66***	2.22	6.40***	2.04
Product Image	43.43***	10.72	6.11**	2.60	9.22***	2.57	7.87***	2.23
Gender (Female)	29.47**	12.93	3.88	4.71	-2.75	4.10	-3.15	3.20
Age	0.40	0.60	0.84***	0.26	0.11	0.23	-0.32**	0.15
Beijing	30.62*	17.55	9.23	6.36	-7.61	5.77	3.35	4.57
Shanghai	-14.17	16.43	9.06	6.45	4.00	6.02	3.22	4.48
Edu	-11.62	8.33	-0.12	3.02	1.29	2.55	-0.68	2.04
Constant	26.57	67.65	182.45***	20.75	237.49***	19.76	185.55***	14.82
Prob > F	0.00		0.00		0.00		0.00	
R-squared	0.27		0.16		0.11		0.11	
N	556		556		556		556	

Note: ***, **, * indicate significance at 1%. 5%, 10% level, respectively.

3.7. Discussion and Conclusion

3.7.1. Discussion of Results

In 2022, it is predicted that Chinese beef imports will continue to grow for the eighth consecutive year. It is predicted that the total beef import value in China will reach 12.49 billion dollars in 2022, which is four times higher than the value in 2017. Furthermore, China reopened to U.S. beef imports in 2017 and the U.S. is becoming the third biggest beef exporter in the Chinese market. At the same time, the Chinese public sentiment towards China is increasing and sentiments are decreasing towards foreign countries. Therefore, the goal of this study was to investigate Chinese consumers’ ethnocentrism levels and their perceptions of both major beef exporting countries and beef products from associated countries, as well as, to evaluate how this affects their preferences and WTP for beef from different countries.

The results regarding ethnocentrism indicate that consumers are more likely to support statements related to “supporting Chinese products” and tend to disagree with statements related to “against foreign products”. These results are in line with findings from Seitz and Roosen (2015), who used the same measurement to elicit consumer ethnocentrism in Europe, and found respondents tend to agree with statements related to “support domestic products”. The mean of the ethnocentrism score in our study is 3.99, which is consistent with the finding from Yin et al. (2019), who measured ethnocentrism in 2014 in China and obtained 3.94 as the average score. However, our mean score is higher than the 3.37 Seitz and Roosen (2015) found, which indicates that Chinese consumers are more ethnocentric than European consumers.

Results for country image indicate that respondents from Beijing, Shanghai, and Guangzhou are very much in favor of China with a mean of 4.45 out of 5. This result is consistent with Cunningham et al. (2020), who reported that 95.5% of respondents were satisfied with the central government in China. Our results also show that Chinese consumers have a neutral opinion towards the U.S. with an average score equal to 3 out of 5. This result is different from Godfarb et al. (2021), who concluded that about 60% of Chinese have an unfavorable view of the U.S. The result of the U.S. Presidential election may explain this difference. As Fang et al. (2022) noted, Chinese evaluations of the relationship with the U.S. plummeted during the Trump era but rebounded somewhat after Biden took office.

The product image results indicate that consumers have the best view of Chinese beef and they have similar views on product image, more specifically, the safety of beef, from the U.S. and Brazil. The difference in distance of transportation could explain this result. For example, Grebitus et al. (2013) found more than 50% of respondents from Germany thought that locally produced apples and wine are safer than those that have traveled many miles.

The main goal of this research is to estimate the effects of ethnocentrism, country image and product image on WTP for COO. We achieved this by regressing ethnocentrism, country image and product image on country-specific individual WTP. The results indicate that consumers who prefer to purchase Chinese products are more likely to pay a premium for Chinese beef and discount beef from developed countries, such as, the U.S. and Australia. This result is similar to the findings from Qing et al. (2012) and Yin et al. (2019), who also concluded that the higher the level of ethnocentrism, the more likely consumers will be to increase their WTP for domestic fruit or organic labels, and will decrease their WTP for foreign fruits or organic labels. Furthermore, our results indicate that consumers are willing to pay a premium for imported beef if they are more in favor of the country where the beef originates from or perceive the beef from a certain country as safer.

3.7.2. Policy Implications

Overall, our study highlights the important effects of consumer ethnocentrism, country image and product image on preferences and WTP for domestic and imported beef. The results suggest that consumers are willing to pay a premium for domestic beef if they have high incentives in purchasing Chinese products, are more in favor of their country and perceive products as safer. Moreover, the perceptions of purchasing foreign products will not affect the WTP for domestic beef. The associated policy implications suggest that the government and domestic beef retailers could try to emphasize the incentives of purchasing the domestic product and positive country or product image on packaging if they want to promote the sales of domestic beef flank. For example, as Kilders et al. (2021) noted, adding labels such as “Proudly Chinese” could be one of the strategies that take advantage of high levels of ethnocentrism. Domestic beef retailers could also attract consumers by information associated with the positive country image to increase consumers’ favorable views of their home country to promote beef sales.

Our study shows that consumers will increase their WTP for foreign beef if they favor the country or the product image associated with that country, and they will discount their WTP if they have high purchasing incentives for Chinese products. Given the growing tension in the global political climate, these results are critical for foreign beef exporters to execute their market strategies. More specifically, beef exporters from either the U.S., Australia, and Brazil could try to attract Chinese consumers by emphasizing the positive country or product images associated with the country to expand their market share in China and strengthening their exports.

3.7.3. Future Research

This study focused on evaluating Chinese consumers’ ethnocentrism, their country and product images towards foreign countries and investigating the relationship between those individual perceptions on consumers’ preferences and WTP for beef originating from different countries. Since our study only focused on preferences and WTP for beef flank using data from three major cities in China, future research surveying consumers from other parts of China and their preferences for other cuts of beef, like steak, will be helpful in further investigating preferences for imported beef and associated market share.

Based on our study, the country image and product image significantly impact WTP for beef from different countries. Future research could deeply explore the factors associated with country image. For instance, it will be fruitful to analyze consumers' perceptions of the cognitive aspect of country image and other aspects of product image, such as, price perception from different countries and how these perceptions will affect favorable views toward those countries. In addition, future research that analyzes consumers' country images using other methods, such as, the affinity survey instrument could also contribute to the literature. Finally, although our study attempted to reduce hypothetical bias by using cheap talk, bias because of the hypothetical setting may still affect our results. Therefore, future research could estimate the effects of ethnocentrism and country image on WTP for imported beef using non-hypothetical stated preference methods in either lab settings or a grocery store setting to verify the results.

CHAPTER 4

EFFECTS OF RISK PREFERENCES AND SOCIAL NETWORKS ON ADOPTION OF GENOMICS BY CHINESE HOG FARMERS

4.1. Introduction

African Swine Fever (ASF), caused by the ASF virus, is a highly contagious disease which leads to almost 100% mortality in domestic and wild pigs of all ages (Galindo and Alonso, 2017; Quembo et al., 2018). Infected pigs usually experience high fever, anorexia, lethargy, weakness, and recumbency, with most of them dying within ten days (Shao et al., 2018). Most importantly, the disease spreads quickly and there is no vaccine or treatment for ASF, yet. Hence, when hogs contract the disease, the situation is dire for the hog producing operation.

After the ASF virus was first identified in Kenya in the 1920s, it spread to Europe and South America in the middle of the last century. The disease was eradicated from Europe temporarily around the 1990s before returning in 2007 (Galindo and Alonso, 2017). Because of the absence of any vaccines or treatments, the disease has a substantial impact on many countries. For example, in Russia more than 800,000 hog deaths were attributed to ASF alone from 2007 to 2017 (Kolbasov et al., 2018).

ASF started spreading in China in August of 2018 with the Ministry of Agriculture and Rural Affairs of China (MARA) reporting the first ASF case in Liaoning, a northeastern province of China. In the next six months, the disease ravaged all of China's hog industry. Until April 2019 MARA reported a total of 129 cases from 31 provinces; the total inventory of hog factories with ASF outbreaks numbering 319,726 by 2019 (Zhang et al., 2019). According to official reports, more than 1.02 million pigs were culled because of the disease, leaving farmers devastated (Xia, 2019). In July 2020, outbreaks of ASF began surging again in certain areas of southern China (Reuters, 2020).

The outbreak of ASF has an enormous impact, not only on China's economy, but also on society, given that pork is the dominant animal-protein source in the Chinese diet. China has dominated world pork consumption for many years. In 2018, Chinese consumers ate more than 55 million tons of pork, comprising approximately half of the pork consumption around the world (USDA, 2019). Average annual pork consumption per Chinese citizen is approximately 40 kilograms. Data from the National Bureau of Statistics (NBS) of China showed that pork covers around 86.27% of meat consumption for all Chinese citizens. Because pork accounts for a large portion of Chinese meat consumption, the pork price has a significant impact on the Chinese Consumer Price Index (Zhao and Wu, 2015).

While consumers are affected by increasing pork prices because of reduced pork supply, hog farmers' livelihood is at stake due to the ASF epidemic. Given this, finding a therapy for this disease is of utmost importance to researchers worldwide. One possible solution would be to use genomics technology (Mazur-Panasiuk et al., 2019). Genomics refers to the mapping and sequencing of genetic material in the DNA of a particular organism, as well as, the use of that information to better understand what genes do, how they are controlled, how they work together, and what their physical locations are on the chromosome (USDA, 2020).

As pointed out by Lee (2005), one important reason for the resistance towards genomics technology in China are concerns regarding the risks of this technology, including concerns involving risk related to food safety and risk related to adopting the new technology. Indeed, risk is an important factor influencing farmers' adoption decisions, shown e.g., by Menapace et al. (2016), Rosburg and Menapace (2018) and Ramsey et al. (2016).

Rosburg and Menapace (2018) analyzed U.S. farmers' fungicide adoption and found people are more likely to adopt fungicides if they expect a higher risk reduction from receiving the fungicide. They applied the lottery by Dohmen et al. (2011) to elicit producers' risk tolerance and show a negative relation between risk tolerance and fungicide adoption. Menapace et al. (2016) studied the impact of risk preference on Italian farmers' crop insurance purchase decision. They used three different methods to elicit farmers' risk preferences: self-assessment using a 10-point Likert scale; a small-stakes gamble test with no contextual framing, and a more time-consuming large stakes gamble with specific framing in terms of income related to actual economic activities. The authors found that farmers' risk preferences calculated from the small-stakes gamble test did not correlate with their crop insurance purchase while farmers who displayed greater levels of risk aversion in the large stakes gamble were more likely to purchase crop insurance. Ramesey et al. (2016) analyzed the effects of farmers' yield risk perceptions on varieties of conservation technologies adopted by crop farmers in Kansas. Results from a bivariate probit model suggest farmers who view these technologies as yield risk-reducing are more likely to adopt conservation technologies such as Continuous No-Till technology, Conservation Crop Rotations technology, and Cover Crops technology. Finally, Lee (2005) states that price risk due to variability in product prices will discourage selected cropping alternatives, and will decrease associated technologies' attractiveness. In addition, the risk related to future access to production inputs, particularly land and water, will decrease the likelihood of farmers adopting technologies or systems that potentially hold positive future returns without being able to confidently claim those benefits (Lee, 2005).

In a broader context, understanding how risk preferences affect adoption of new technologies, such as, genomics technology can help to shed light on other areas where we try to understand how individuals will adopt new technologies during times of crisis. How individuals will make their adoption decisions, and how their risk preferences affect their adoption decisions under disease outbreak, are important for stakeholders to understand if they want to release their new technologies to the market.

In addition to risk preferences affecting decision making, previous studies have shown that social relationships affect behavior (Marsden and Friedkin, 1993, Granovetter, 1973). More generally, the ways in which individuals are influenced by their social interactions depend on the members in their social networks (Marsden and Friedkin, 1993; Lippitt et al., 1952). In this study we look at hog farmers' social networks to understand how other hog farmers in their networks could potentially influence their technology adoption decisions. A network can be understood as a "channel of communication" (Alba and Kadushin, 1976) where information, opinions and peer behavior are processed and influence network members (Marsden and Friedkin, 1993). Such diffusion networks, i.e., the links between actors in these networks, can be measured by sociometric methods, where it is common to specify the number of sociometric partners that can be named by a respondent (Rogers, 2003). Hence, we applied the sociometric method by asking hog farmers to list three farmers with whom they usually discuss hog health issues. In doing so we follow previous studies by Conley and Udry (2001), Kabunga et al. (2012) and Matuschke and Quaim (2009) that have applied this approach. For example, Matuschke and Quaim (2009) asked farmers to name three persons to whom he or she talks most frequently about agricultural decisions. They found that social network members have a significant and positive effect on farmers' technology adoption decisions. A downside of this approach is that it leads the respondent to name only their strongest network members and hence others that they may exchange important information with could be ignored because of lower communication frequency. This relates back to Granovetter's (1973) "strength-of-weak-ties" theory that describes that these less-frequent network partners may be particularly crucial in diffusion (Rogers, 2003). To account for the effects from members they communicate less often with, we employ the centrality measures degree, closeness, and betweenness, to investigate the impact of social relationships when analyzing adoption behaviors of hog farmers. We hypothesize that if a hog farmer is well-connected with other hog farmers who want to adopt the technology, he or she is more likely to also adopt the technology. We also hypothesize that hog farmers will share similar characteristics like risk preference and adoption behavior with persons they talk to most frequently about hog health issues. Hence, it is important to understand the social relationships among hog farmers.

Against this backdrop, our objective is two-fold. Our first objective is to analyze farmers' risk preferences and attitudes towards genomics technology, and to investigate how these risk preferences and attitudes affect their willingness to adopt genomics information to breed hogs that are more resistant to diseases like ASF. Our second objective is to shed light on hog farmers' social networks to understand how social influence can potentially affect (hog farmer) decisions related to new technologies, such as, genomics, in the presence of a disease outbreak. Insight into hog farmers' relationships highlights how peer effects affect their decisions.

4.2. Background

4.2.1 Genomics

Genomics technology has been widely used in stopping the spread of hog disease since the early 1990s when pig breeders removed deleterious genes, such as, the halothane gene (HAL), which causes porcine stress syndrome, and the napole gene (RN-) from their herds (Rothschild et al., 2010). Another example of successful application of genomics technology is the Porcine Reproductive and Respiratory Syndrome (PRRS, also known as "Blue Ear disease"), a severe hog disease that spread across the world dramatically in the 2000s. In 1987, PRRS was first detected in the United States. Since then, it "has cost the global hog industry an estimated $6 million per day worldwide" (Day, 2015). In 2015, the spread of the disease was controlled using genomics technology to isolate the protein, CD163, which causes PRRS to spread throughout the pig (Whitworth et al., 2016).

Previous studies have shown that artificial insemination, one of the breeding technologies widely used in the hog industry, is among the most cost-effective ways to improve the global swine population by increasing pigs' disease resistance properties (Gerrits et al., 2005). Hog farmers can purchase high-quality semen, like semen with genomics technology, without the investment in and expenses associated with owning a boar. However, compared to other capital-intensive technology, artificial insemination is a management-intensive technology that requires special training, which makes the availability of quality labor important for effective implementation (Gillespie et al., 2004).

In order to obtain the benefit of genomic technology in the agricultural industry, the Chinese central government has issued a clear signal encouraging and supporting research and adoption of genomics technology. The state's No.1 Central Document in 2015 pledged more government support for research on Genetic Modification (GM) technology. In addition, the No.1 Central Document identified the need for the nation to modernize agriculture through scientific and technological innovation and implementation of smart technologies in 2017 (Wang, 2015; Zhang et al., 2019). However, despite the support from the central government, literature that analyzed the adoption of genomics technology in China found that Chinese farmers are reluctant to adopt genomics technology. Chinese people's attitudes towards genomics technology are an essential factor driving this result (Deng et al., 2017; Huang and Peng, 2015; Xu et al., 2016). A nationwide survey found that 46.7 percent of respondents viewed Genetically Modified Organisms (GMOs) negatively, with 14 percent believing it was a form of bioterrorism aimed at China (Chow, 2019). Xu et al. (2016) analyzed farmers' willingness to adopt GM rice before its commercial release and found only one-third of the respondents willing to adopt the new rice variety, and more than half of the remaining farmers were uncertain. They also found that while farmers' attitudes on environmental impact were not significant, the concerns on health and economic benefits were crucial to their GM rice adoption decisions. Huang and Peng (2015) analyzed consumer perception on GM food safety and found approximately 45% of the respondents consider GM food as being unsafe. Deng et al. (2017) studied 160 Chinese agribusiness managers' attitudes towards GM foods from 2013 to 2014, and found that 61% of them hold negative views towards GM foods. The number is even higher than the percentage of consumers who thought GM food was unsafe (Huang and Peng, 2015). Huang et al. (2005) analyzed insect-resistant GM rice adoption in China and found there are positive impacts of the insect-resistant GM rice on productivity and farmer health, which could also affect farmers' attitudes toward genomics. The findings from these different studies underline a rather negative attitude towards some new technologies and this might carry over to technologies such as genomics. Hence, in this study we test hog farmers' attitudes towards genomics technology that could potentially reduce the risk of hogs being infected with ASF.

4.2.2. Risk Preferences

Previous literature has analyzed farmers' risk preferences related to their technology adoption decisions. Gillespie et al. (2004) analyzed US hog farmers' adoption decision on breeding technology, and found more risk averse farmers are more likely to adopt the risk-reducing technology. Brick and Visser (2015) found that small-scale farmers in South Africa who are more risk averse are more likely to adopt traditional agriculture, such as, using traditional seeds, and are less likely to use modern farming inputs, such as, high-yield varieties despite the availability of insurance. Hailu et al. (2017) analyzed Canadian farmers' risk attitudes using a risk tolerance measure that combines psychological questions and lottery questions, and found that farmers with a higher risk tolerance are willing to pay more for genotyping services. Studying Chinese farmers' adoption decisions on BT Cotton, Liu (2013) found more risk averse farmers tend to adopt the technology later. Recently, Gao et al. (2020) analyzed the new agricultural technology extension mode adopted in China and found farmers who have a greater acceptance of risk are more likely to adopt the new technology extension mode. In sum, all of these studies found that more risk averse farmers are less likely to adopt new technologies early. However, while there are several studies covering a number of issues, so far, research focused on technology adoption by small scale hog producers in developing countries like China is scarce, and even less research is available focusing on farmers' risk preferences related to their adoption decisions under an actual disease outbreak like ASF. This is important because the current ASF crisis would require actual decisions from farmers if the genomics technology was available rather than the crisis being a hypothetical scenario. Hence, the fact that hog farmers in China lost more than 1.2 million hogs has to be kept in mind when trying to understand how hog farmers' risk preferences and attitudes affect their willingness to adopt genomic information when breeding hogs that are more resistant to diseases like ASF. The main objective of our case study is to help close the gap in the literature by providing information on how risk preferences affect technology adoption in a situation of crisis.

4.2.3. Social Network Analysis

Previous literature has found that farmers' social networks have a significant impact on farmers' daily life, including their technology adoption decisions (Bandiera and Rasul, 2006; Conley and Udry, 2010; Foster and Rosenzweig, 1995; Holloway et al., 2002; Kabunga et al., 2012; Krishnan and Patnam, 2014; Ward and Pede, 2015). For instance, Wang et al. (2021) explored the impact of social networks on household livelihood resilience in China and they found farmers' social networks have positive impacts on livelihood resilience in that farmers with higher degree and betweenness centralities are more resilient. Xia et al. (2020) also showed the positive effect of social networks when they examined social network effects on peasant households' land use decision-making. Johny et al. (2017) found social networks can affect income diversification among rural households in India significantly. Furthermore, Gava et al. (2017) applied social network analysis to evaluate stakeholders' importance in technology adoption and diffusion using the example of Italy. The authors found upstream industry like plant dealers have the most significant impact on knowledge diffusion across adopters compared to other stakeholders including farmer unions, universities, and research centers. When studying forest owners in Finland, Vainio et al. (2018) found that where forest owners seek information differed based on the type of contract used. Conley and Udry (2016) analyzed the effect of learning from other farmers in a social network on innovations for input use for farmers who cultivate pineapple in Ghana and found farmers are more likely to adopt innovative inputs, like new fertilizer, after being informed that neighbors achieved higher profits using the new fertilizer. Hollway et al. (2002) estimated high yield variety rice adoption in Bangladesh and found strong, positive neighborhood effects on technology adoption among Bangladeshi rice farmers. Krishnan and Patnam (2014) studied network effects on adoption of new fertilizer and seed for farmers in Ethiopia and found that social network effects play an important role on farmers' technology adoption decisions, and this effect is even higher than the effect of extension agents visiting. Kabunga et al. (2012) analyzed the impact of social networks on tissue culture banana technology in Kenya and found farmers' individual social networks played an important role for technology adoption decisions. Moreover, they found that the more adopters in a farmer's personal network, the less likely the farmer himself adopts this as well, which could indicate that the technology is not beneficial for all. Ward and Pede (2015) studied how a social network affects the adoption of hybrid rice in Bangladesh taking into account geographic distance. They find that farmers are more likely to adopt hybrid rice if their networks include nearby hybrid rice adopters compared to farmers who have networks of more distant hybrid rice adopters. In another study, Bandiera and Rasul (2006) captured the impact of social networks on the adoption decision regarding sunflowers in Mozambique and found social networks have a positive effect on the adoption decision when there are only a few adopters in the network, but this changes to a negative effect when there are many adopters in the network. Moreover, the authors also researched the effect of closeness in relationships on adoption decisions. They stated that adoption decisions are more correlated with the network consisting of close family and friends compared to religion-based networks that are less close to each other, both in geographic and relationship distance. Given this previous evidence of peer effects on decision making, we test how social networks affect willingness to adopt genomics.

4.3. Methodological Background

4.3.1. Design of the Study

To test the effects of risk preferences and social networks on adoption of genomics technology by Chinese hog farmers, we collected data using a face-to-face case study with a standardized survey instrument. We interviewed hog farmers in two locations in China. We conducted our case study in a district in Chongqing, which is one of four municipalities in China. It is a big city located in southwestern China, with a population of more than 30 million. Chongqing is famous for its hog industry from production to consumption, and the outbreak of ASF had a massive effect on the hog industry in Chongqing. The data from the National Bureau of Statistics of China (NBS) indicate Chongqing produced more than 17.58 million pigs in 2018, ranking eleventh place for all provinces. This means that

Chongqing produced 0.6 head of pigs per citizen in 2018, which is much higher than the number of pigs produced per Chinese citizen in other areas of the country. Data show the average pork consumption for each Chongqing citizen reached 74 lbs. annually (Sina, 2019). This number ranks second among all Chinese provinces. In addition to collecting data in Chongqing, the case study was carried out in a village in the Hebei province. Hebei province is famous for its hog production industry, located in the northern part of China. Data from the Ministry of Agriculture (MOA) indicate that Hebei province produced more than 34.5 million pigs in 2016, ranking eighth for all provinces in China. However, Hebei citizens are less in favor of pork, with an average pork consumption of 30 lbs/year, ranking 22nd out of all 31 provinces (Sina, 2019). By comparing the results from Chongqing to Hebei, our objective is to test how generalizable our results are, accounting for regional effects.

Our interviews in summer of 2019 led to a total of 46 usable survey results from the two locations. We collected 65 completed surveys from three different counties in Chongqing. After eliminating 32 surveys that were not filled out by hog farmers' themselves but had been filled out by neighboring farmers, and one survey of a producer whose revenue from raising hogs did not cover more than 50% of his total income in 2018, 32 valid surveys remained for data analysis from Chongqing. Raising hogs is extremely popular in Chongqing and almost every rural family raises pigs. Most of them just raise a few hogs to provide food for themselves, especially during Spring Festival, a traditional Chinese Lunar New Year. In this study, we tried to collect data only from certified hog farmers who earned more than 50% of their total income from raising hogs. In addition, a total of 14 valid surveys were collected from Hebei. While at first glance the number of usable observations may seem small, several things need to be kept in mind. First, interviewing hog producers in China during the ASF outbreak presented a challenge, with most of them refusing to meet with other people because they were afraid of bringing ASF to their farms. Second, these numbers are comparable to other explorative, qualitative interviews, and expert interviews with sample sizes often being below 30, such as studies by Iles et al. (2020), Lachal et al. (2012), Van Gilder & Abdi (2014), Bennet et al. (2013), Sonneville et al. (2009), Mitter et al. (2019), Hunold et al. (2017), and Takashi et al. (2016), where the sample sizes range from n=12 to n=22.

4.3.2. Data Collection

As mentioned, we obtained the data for our case study using standardized surveys. The questionnaire covered demographic information, such as gender, age and education, as well as operation characteristics of the hog farms including hog farming type, revenue from hog raising, purchasing insurance and hiring labor. The main part of the survey focused on hog farmers' willingness to adopt genomics technology, questions related to their attitudes towards genomics technology, the Dohmen et al. (2010) risk preference measure, and social networks of hog farmers related to the ASF outbreak. The main components of the survey instrument are described in the following sections.

4.3.2.1. Willingness to Adopt Genomics Technology

To measure hog farmers' willingness to adopt genomics technology we first asked whether they would be interested in purchasing semen resistant to ASF if it was produced using genomics. Those who answered "yes" were then asked how soon they would adopt it when made commercially available. This aims to gauge their willingness, assuming that those who would adopt it immediately would be much more likely to actually adopt than those who answered “after 10 years”. The answer categories included were “Immediately,” “After 1 year”, “After 2 years”, “After 5 years” and “After 10 years”.

To further understand hog farmers’ willingness to adopt the technology, we asked a second question where participants had to indicate their likelihood of adopting this technology: “*Latest research shows that the use of genomic information in breeding could reduce the incidence of African Swine Fever. Given this information, please indicate your likelihood of adopting this technology given the below reduction of African Swine Fever in %*”. The answer categories in percent ranged from ASF being reduced by 0%-19%, 20%-39%, 40%-59%, 60%-79%, or more than 80%. Possible answers ranged from 1= Definitely Not to 5= Definitely.

4.3.2.2. Attitudes affecting the Adoption of Genomics Technology

To identify attitudes that may affect hog farmers’ adoption decisions, they were asked to evaluate a number of reasons that might influence their decisions with the question “*Please indicate how important the following aspects are to you in adopting the use of genomic information for the selection of African Swine Fever (ASF) resistant hogs on your farm?*” Possible answers ranged on a 5-point Likert-scale question from 1= Very unimportant to 5= Very important. Examples of the statements used are: *Contributes to the protection of resources for future generations; Does not increase workload; The technology can be tested with small batches of animals on the farm first*. A full list of all statements can be found in Appendix E.

4.3.2.3. Risk Preference Measure

Lottery methods such as Holt and Laury’s (2002) or Dohmen et al.’s (2010) instruments are popular to elicit and measure risk attitudes (Barham et al., 2015; Freudenreich and

Mußhoff, 2018; Qiu et al., 2014; Zhao and Yue, 2020). In this study we employed the lottery by Dohmen et al. (2010) to elicit hog farmers' risk preferences. In this lottery, participants were asked to make choices between a lottery option and a safe option in a table with 20 choice situations. The lottery option is fixed in the amount and related possibility in each row, and the amount in the safe option increases from row to row. Subjects were asked to choose between the lottery option and the safe option one row at a time. Given the constant increase of the amount of the safe option, respondents should choose the lottery option starting from the top of the table and should switch to the safe option in the middle, and then continue to choose the safe option if they have monotonic preferences. Based on Dohmen et al. (2010), the switching point in the lottery is informative of a subject's willingness to take risks.

In the risk preference measure we asked, "*Imagine you are choosing a lottery ticket. There are two different lottery tickets with different amounts of rewards per the chance probabilities. Indicate whether you would prefer Option A or Option B, i.e., one decision for each situation.*" The choice situations are presented in Appendix F. Option A is the fixed lottery that respondents could either win ¥1,500 or 0 in RMB (at the time, 1 RMB ~ 0.14 U.S. dollars) and Option B is the safety payment starting with 0 and increasing ¥ 50 from row to row up to ¥ 950 in row 20. Given the average winning amount for playing the lottery is ¥750 in all rows, a risk-neutral subject is assumed to choose the lottery starting in the first row and switch to the safe option in row 16 when the amount of the safety payment is equal to the average revenue of choosing to play the lottery. A risk-seeking person should switch to the safety payment after row 16, and risk-averse people are assumed to switch to the safety payment before row 16. A risk-seeking (or risk-prone) person who likes taking risk should switch to the safety payment later than row 16, where the safety payment was higher than the expected value of playing lottery and vice versa.

4.3.2.4. Social Network Analysis

To identify the hog farmers' social networks and to measure the closeness of their relationships with other hog farmers, we first asked hog farmers to list names of their top 3 other hog farmers[3], with whom they discuss hog health with. See Appendix E for the survey instrument. The questions regarding their relationships with others were phrased towards hog health because we focus on genomics technology to reduce ASF. We infer that those are likely individuals they would get advice from regarding the adoption of a new technology, such as, genomics to reduce the risk of ASF infections.

4.3.3. Data Analysis

4.3.3.1. Social Network Analysis

Core/Periphery Analysis determines the location of each actor within a network based on the physical center. Core/periphery analysis identifies who belongs to the core and who belongs to the periphery (Borgatti and Everett, 2000). Actors who belong to the core are those who are related not only to each other but to all other actors in the network. In contrast, actors who are not close to the center are in the periphery (Bogatti and Everett, 2000; Grebitus, 2008). Belonging to the core or periphery affects how much a farmer can influence or be influenced regarding their attitudes and behaviors. For instance, farmers belonging to the core are able to receive and transmit more information than those belonging to the periphery. Hence, if a farmer belonging to the core is favorable towards

[3] In the survey, we asked hog farmers to list the names of their top 3 hog farmers, veterinarians, and sales agents. However, in this analysis we only include data related to their top 3 other hog farmers.

genomics, this farmer can transmit positive information to all farmers in his network. Information about this enables stakeholders to become more efficient in identifying which actors will be useful to transmit information.

Centrality is a key measure of the "power" of a single node in aggregated social networks (Wasserman and Faust, 1999; Freeman, 1979). When transmitting information and influencing other actors' attitudes or behaviors, centralities identify actors who are most efficient in doing so. For instance, the more power a single node has, the closer it is to the "center" of the action in a network, and the higher the impact of this actor on the entire social network (Hanneman and Riddle, 2005). There are three key measures: degree, closeness and betweenness centralities.

Degree Centrality measures the "power" of an actor by the number of ties this actor has. The higher number of ties, the more connected an actor is with others; hence, this actor will be able to receive information from several sources and can also distribute information to a great number of other actors. With regards to technology adoption, this actor has a higher number of connections with others, which means such an actor could obtain information about the new technology from many other people – compared to an actor with a lower degree centrality who is less well-connected. Degree centrality C_D of an actor (node) P_d can be calculated following Freeman (1979) by

$$\mathrm{C}_D(\mathrm{P}_d) = \sum_{e=1}^{I} a(P_e, P_d) \; for \; e \neq \mathrm{d} \qquad (1)$$

$\mathrm{a}(P_\mathrm{e}, P_d)$ is a dummy variable equal to 1 if $\mathrm{P_e}$ is directly connected to $\mathrm{P_d}$, zero otherwise. I is the number of actors in the network except $\mathrm{P_d}$ himself (Freeman, 1979).

Closeness Centrality measures how connected an actor is, i.e., how easily he can receive/transmit information. Closeness centrality defines how powerful an actor is by accounting for not only the relations with actors who are directly connected, but also the indirect relations with actors who are not directly connected. In other words, closeness centrality is used to check how quickly the information will flow through the whole network. For example, farmers with higher closeness centrality are useful for institutions or governments when they hope to diffuse information of new technology to the entire network with shorter time (or lower costs).

The idea behind closeness centrality is that actors who are able to be reached by other actors at shorter path lengths have favorable positions (Hanneman, 2005; Jackson, 2008). For instance, if the information of new technology goes directly from sender to receiver, this receiver has an advantage to obtain more sufficient information about the technology over a receiver who can only be reached via multiple senders. Therefore, the "farness" of the actor; the aggregate distance between the actor to all other actors in the social network; is the major component of the closeness centrality. Because of the variety of ways to define farness, there are several approaches to calculate closeness centrality. The Freeman geodesic path approach is the most common way. Here, "farness" is defined as the sum of the lengths of the shortest distance from each actor to all other actors in the social network. In this case, the closeness centrality C_C of a node P_d is calculated by

$$C_C(P_d) = [\sum_{e=1}^{I} r(P_e, P_d)]^{-1} \ for\ e \neq d \tag{2}$$

$r(P_e, P_d)$ is the number of lines in the geodesic linking nodes P_e and P_d. I is the number of actors in the network (Knoke and Kuklinski, 1982).

Betweenness Centrality assumes that an actor will have more "power" if lying on the geodesic paths between other pairs of actors in the network (Hanneman, 2005; Jackson, 2008). In other words, the more someone depends on other actors in order to connect with network members, the less power that node has. Betweenness centrality is calculated as the probability that more than one geodesic path exists between pairs of actors. Betweenness centrality C_B of a node P_d is calculated by

$$C_B(P_d) = \sum_e^t \sum_f^s b_{ef}\,(P_d)\; for\; (e < f) \neq d, \text{and } b_{ef}(P_d) = \frac{g_{ef}(P_d)}{g_{ef}} \qquad (3)$$

t and *s* are the number of nodes in the network and g_{ef} is the number of geodesic paths from point e to point *f* that contain node P_d. Therefore, $b_{ef}(P_d)$ represents the probability that P_d falls on a randomly selected geodesic connecting *e* and *f* (Freeman, 1979).

4.3.3.2. Principal Factorial Analysis

To measure the effect of hog farmers' attitudes on their technology adoption decisions, we apply principal component factor analysis to reduce the number of statements resulting from the question *"Please indicate how important the following aspects are to you in adopting the use of genomic information for the selection of African Swine Fever (ASF) resistant hogs on your farm?"* (see section 4.3.2.2.) into uncorrelated factors. Based on the Kaiser criterion, factors with eigenvalues equal or higher than 1 were retained (Kaiser, 1958). We then applied the varimax rotation approach to obtain factors that are not correlated to each other. The varimax rotation approach also allows us to create indexes without inter-correlated components and enables the maximization of variance of the loadings (Kilders et al., 2021).

4.3.3.3. Ordered Probit Model

In our study, we measure the time for hog farmers to adopt genomics technology. The question is phrased as "*Assuming the costs are the same, would you be interested in purchasing semen made using genomics that has demonstrated resistance to African Swine*

Fever (ASF)?" The answer categories are *Yes/No*. The follow-up question is, "*If YES, how soon would you adopt this technology when it is made commercially available?*" The answer categories ranged from Never to Immediately. Hog farmers who chose "No" in the first question are merged with those who answer "never" to the follow-up question. Thus, we have six categories to indicate the time that it would take hog farmers to adopt the technology once it is made commercially available.[4] Given the ordinal data structure, we then use an ordered probit model to analyze the effect of hog farmers' risk preferences, social networks, and their attitudes on the willingness to adopt ASF resistant semen produced using genomics.

The ordered probit model considers the ordinal nature of the dependent variable. We follow Greene (2012, pp. 787-791) to explain the unobserved preference of hog farmer *i* to choose a certain time to adopt the semen in the ordered probit model by

$$y_i^* = \beta x_i + \varepsilon_i \tag{4}$$

where y_i^* is the observed ordinal variable, denoted as the time for hog farmers to adopt the technology after it is made commercially available. x_i is a vector of independent variables including hog farmer experience in a hog operation in years, age, education level, his risk preference obtained from the lottery, network measures, and his attitude towards the genomics technology; β is a vector of parameters to be estimated associated with x_i; and ε_i are unobserved factors and assumed to be normally distributed. In the ordered probit model, the relationship between the observable y_i with the latent variable y_i^* is

[4] The question in the survey instrument had six categories, however, no respondent chose the category "adopt genomics after 10 years", hence, in the remainder of the analysis we work with five categories.

$$
\begin{aligned}
&y_i = 1 \; if \; y_i^* \leq u_1 \\
&y_i = 2 \; if \; u_1 < y_i^* \leq u_2 \\
&y_i = 3 \; if \; u_2 < y_i^* \leq u_3 \\
&y_i = 4 \; if \; u_3 < y_i^* \leq u_4 \\
&y_i = 5 \; if \; u_4 < y_i^* \leq u_5
\end{aligned} \tag{5}
$$

where u_j are unknown parameters to be estimated with β. By normalizing the mean and variance of the error term u_1 to zero and one, the probabilities for y_i are

$$
\begin{aligned}
&Prob(y = 1 \mid x) = \Phi(u_1 - \beta x_i) \\
&Prob(y = 2 \mid x) = \Phi(u_2 - \beta x_i) - \Phi(u_1 - \beta x_i) \\
&Prob(y = 3 \mid x) = \Phi(u_3 - \beta x_i) - \Phi(u_2 - \beta x_i) \\
&Prob(y = 4 \mid x) = \Phi(u_4 - \beta x_i) - \Phi(u_3 - \beta x_i) \\
&Prob(y = 5 \mid x) = 1 - \Phi(u_4 - \beta x_i)
\end{aligned} \tag{6}
$$

where Φ is the cumulative distribution function, and the cut-off points u_j determine the alternative of y being chosen. For example, the alternative 1 is chosen if the probability that the latent variable y_i^* is equal to or below u_1 and if y_i^* is located between u_1 and u_2, then the alternative 2 will be chosen (Areal et al., 2012). Therefore, the relationship between the observed variable y_i and the latent variable y_i^* will help us to analyze hog farmers willingness to adopt genomics. The equation below shows exemplarily the modeling approach:

$$
y_i^* = \beta_{atti1}x_{1i} + \beta_{atti2}x_{2i} + \beta_{atti3}x_{3i} + \beta_{lottery}x_{lotteryi} + \beta_{city}x_{city} + \beta_{educ}x_{educi} + \beta_{age}x_{agei} + \beta_{exp}x_{expi} + \beta_{cent}x_{cent} + \beta_{core}x_{core} + \beta_{SNA\_adopt}x_{SNA\_adopt} + \varepsilon_i \tag{7}
$$

where y_i^* represents the time to adopt genomics. We use the time to adopt in order to differentiate between those who are more likely to adopt and those who are less likely to adopt. Here, y_i^* = *1* represents hog farmers who answered "No" to the question *"Assuming the costs are the same, would you be interested in purchasing semen made using genomics that have demonstrated resistance to African Swine fever (ASF)?"* and y_i^* equal or greater than 2 represents hog farmers who answered "YES" to the above question. In addition, those who answered Yes, were then asked the following: "*If YES, how soon would you adopt this technology when it is made commercially available?".* Their evaluations about the time to adopt this technology is based on a Likert scale with four time periods: 2 = "After five years", 3= "After two years", 4= "After one year", or 5="Immediately."

$\beta_{atti1}, \beta_{atti2}, and\ \beta_{atti3}$ are the coefficients for the three factors obtained from principal factor analysis. $\beta_{lottery}$ is the risk preference coefficient, which is elicited from the lottery question. β_{educ}, β_{age}, and β_{exp} are coefficients for education level, age and years in hog raising experiences of the respondent, where education level is a categorical variable from 1 to 4, representing the highest education completed from elementary school to undergraduate level. β_{city} is a categorical variable, which equals to 1 if hog farmers are from Hebei and equals to 2 if hog farmers are in Chongqing. β_{cent} and β_{core} are social network measures, where β_{core} is a dummy variable equal to one if the hog farmer is in the core and zero otherwise and β_{cent} represents centrality measures (degree, closeness and betweenness). β_{SNA_adopt} takes into account the adoption willingness of other hog farmers in an individual's network (as discussed in Section 3.2.4, each individual indicated their top 3 other hog farmers with whom they discuss hog health with). This variable is generated by summing up $y_i^*$for these hog farmers, that the individual is directly related to. This is then divided by the number of "other" hog farmers, since not every individual listed three other hog farmers. In sum, this variable represents the average time to adopt genomics of other hog farmers that the individual indicated to discuss hog health with.

4.4. Results

4.4.1. Sample Characteristics

Table 4.1 shows the summary statistics from Chongqing and Hebei. 24 out of 32 hog farmers in Chongqing run operations with hogs from farrow to finish, seven focus only on the feeder process, one hog farmer manages hogs from farrow to wean. All 14 hog farmers in Hebei province manage hogs from farrow to finish. The results indicate that some features are similar across the two regions. For example, most hog farmers are males with lower education levels compared to the average level of education, which would be similar to middle school. Most of the respondents are older than 40 years of age. At the same time, most of them are experienced in raising hogs with the average years of raising hogs being ten. There are some differences between the different cities, though. For example, half of the farmers from Chongqing are at least 50 years and more than 34% of the farmers from Chongqing have at least 15 years of experience in hog raising while around 36% of hog farmers from Hebei are at least 50 years and 2 out of 14 hog farmers interviewed in Hebei have at least 15 years of experience in hog raising.

Table 4.1. Summary Statistics from Chongqing and Hebei

Hog farmers from	Chongqing (n=32)		Hebei (n=14)	
	No. of hog farmers	Percentage	No. of hog farmers	Percentage
Operation type				
Farrow-to-finish	24	75%	14	100%
Farrow-to-wean	1	3.2%	0	
Feeder	7	21.88%	0	
Education level				
Elementary school or below	4	12.5%	2	14.29%
Middle School	24	75%	6	42.86%
High School	3	9.38%	5	35.71%
College degree	1	3.12%	1	7.14%
Gender				
Male	31	96.88%	14	100%
Female	1	3.12%	0	0
Age in years				
35-39	2	6.25%	3	21.42%
40-44	8	25%	2	14.29%
45-49	6	18.75%	4	28.57%
At least 50	16	50%	5	35.71%
Experience in years				
0-4	6	18.75%	0	0
5-9	6	18.75%	3	21.43%
10-14	9	28.13%	9	64.29%
15-19 years	7	21.88%	1	7.14%
At least 20 years	4	12.5%	1	7.14%

Note: * Total revenue is obtained after subtracting operation costs and adding income from other sources.

4.4.2. Willingness to Adopt Genomics

Hog farmers were asked to evaluate their willingness to adopt semen with genomics technology. Three hog farmers out of 46 said they would not want to purchase semen with genomics even if it demonstrated resistance to ASF. The remaining 43 stated that they would be willing to adopt this technology. The follow-up question asked how soon they would adopt to understand the timeframe within genomics could be implemented. Table 4.2 shows the timeframe of adoption. The three farmers who indicated they do not want to purchase semen with genomics were assigned to the category “Never”. Of the 43 hog farmers who showed interest in purchasing semen with genomics, more than half (22) indicated they would purchase the semen immediately after being commercially available. Table 4.2 also reveals that six hog farmers would want to adopt after one year and 10 after two years. None of the farmers would want to wait ten years or longer to adopt. Hence, most of the surveyed hog farmers would be willing to adopt the semen made using genomics if it has proven ASF resistance. Given that around 90% indicated they would adopt within two years, we consider them to be very likely adopters if the technology was to be made available.

Table 4.2. Willingness to Adopt Semen with Genomics Traits

	No. of hog farmers	Percentage
Never	3	6.52%
After ten years	0	0%
After five years	5	10.87%
After two years	10	21.74%
After one year	6	13.04%
Immediately	22	47.83%

Note: Survey question: *Assuming the costs are the same, would you be interested in purchasing semen made using genomics that have demonstrated resistance to African Swine fever (ASF)? Yes/No; If YES, how soon would you adopt this technology when it is made commercially available?*

We also inquired whether adoption is related to the efficacy of the genomics semen. Table 4.3 shows that hog farmers' willingness to adopt semen with genomics increases with the increase in maximum reduction in ASF infection. More specifically, many hog farmers switch from definitely not adopt to adopt when the semen can demonstrate at least a 60% reduction in ASF infection, and 26 out of 44 (roughly 60%) hog farmers will adopt or definitely adopt the semen if it demonstrates at least 80% resistance to ASF.

Table 4.3. Relationship Between Genomics Efficacy and Adoption Rate

ASF reduced by	Definitely Not (1)	(2)	(3)	(4)	Definitely (5)
0%-19%	42	1	0	0	1
20%-39%	34	9	1	0	0
40%-59%	35	8	10	1	0
60%-79%	11	15	5	10	3
80%-100%	0	3	15	11	15

Note: Survey question: Latest research shows that the use of genomics information in breeding could reduce the incidence of African Swine Fever. Given this information, please indicate your likelihood of adopting this technology given the below reduction of African Swine Fever in %.

4.4.3. Attitudes towards Adoption of Genomics Technology

Table 4.4 presents the results of hog farmers' attitudes towards adopting genomics technology. Statements related to "safety," including breeding safety and food safety, are the most important factors impacting attitudes towards technology adoption. Almost all participants think these are important factors, when deciding on whether or not to adopt the technology, and 30 out of 44, around 68%, of hog farmers think "breeding safety" (corresponding to the statement "Does not increase problems such as inbreeding and increased susceptibility to other diseases") is very important. On the other hand, statements related to workload are not important when making adoption decisions. 32 out of 44, around 73%, of the hog farmers think that whether or not genomics technology requires additional training is very unimportant or unimportant, and only approximately one-third of them believe that an increase in workload is at least important in affecting their decision to adopt the technology.

Table 4.4. Attitudes Towards Adoption of Genomics Technology

Attitudinal statement	Very unimportant	Unimportant	Neutral	Important	Very important
Does not increase cost or even reduce cost	0%	0%	15.91%	50.00%	34.09%
High accuracy on breeding values	0%	0%	20.45%	52.27%	27.27%
Does not increase problems such as inbreeding and increased susceptibility to other diseases	0%	0%	2.27%	29.55%	68.18%
Ensures the production of safe products	0%	0%	2.27%	31.82%	65.91%
Is not linked to a high risk of malfunctioning	0%	0%	6.82%	27.27%	65.91%
Does not require additional training	22.73%	50.00%	18.18%	6.82%	2.27%
Contributes to the protection of resources for future generations	0%	9.09%	11.36%	40.91%	38.64%
The technology can be tested with small batches of animals first	0%	11.36%	50.00%	29.55%	9.09%
Does not increase time spending on diseases controlling	2.27%	0%	29.55%	50.00%	18.18%
Ensures competitiveness of your farm	0%	2.27%	9.09%	38.64%	50.00%
Does not increase workload	2.27%	20.45%	43.18%	27.27%	6.82%
Is compatible with the values of society and consumers	0%	6.82%	20.45%	40.91%	31.82%

Next, we apply principal component factor analysis to reduce the number of statements into uncorrelated factors that display hog farmers' attitudes towards technology adoption. The Kaiser-Meyer-Olkin criterion of sampling adequacy (Kaiser, 1970) is 0.82, which is considered to be meritorious. In order to reduce potential multicollinearity when including the attitudes in the ordered probit model, the factors were extracted with eigenvalues greater than one using orthogonal varimax rotation (Kaiser, 1958). The factor analysis generated a three-factor solution, which explains 70.29% of the total variance of hog farmers' attitudes. The factor loadings are presented in Table 4.5. Cronbach's alpha (Cronbach, 1951) assesses the reliability of the scale composed of the variables, and the results are reported in Table 4.5. Cronbach's alpha results for the three factors are 0.89 (good), 0.79 (acceptable) and 0.64 (questionable).

The first factor is associated with hog farmers' concerns about breeding by adopting genomics technology. Breeding is an important part of a hog operation. Genomics technology has previously been adopted in hog breeding, and has a huge impact on revolutionizing pork production efficiency (Gillespie et al., 2004). This factor is hypothesized to have a positive effect on adoption of genomics technology. The second factor is associated with resource management perceptions of genomics technology adoption. Besides the breeding information of this technology, hog farmers also pay attention to resource investment when adopting it, including time spent on additional training and disease control. Since most of the hog farmers in our sample are small-scale operations, this factor is hypothesized to have less impact on technology adoption. The third factor is competitiveness including farmers' expectations of competitiveness. One potential reason for hog farmers to adopt the technology is to improve their hog farm's competitiveness, which could increase their revenues. The competitiveness factor is hypothesized to impact hog farmers' technology adoption positively.

Table 4.5. Factor Loading Results

Attitudinal statement	Factor 1	Factor 2	Factor 3
	Breeding	Resources	Competitiveness
Cronbach's alpha	0.89	0.79	0.64
Enables cost neutrality or even cost reduction	0.88		
High accuracy on breeding values	0.76		
Does not increase problems such as inbreeding and increased susceptibility to other diseases	0.74		
Ensures the production of safe products	0.64		
Is not linked to a high risk of malfunctioning (reliability)	0.58		
Does not require additional training		0.81	
Contributes to the protection of resources for future generations		0.70	
The technology can be tested with small batches of animals on the farm first		0.63	
Does not increase time spending on disease controlling		0.67	
Ensures competitiveness of your farm			0.78
Does not increase workload			0.70
Is compatible with the values of society and consumers			0.47

4.4.4. Risk Preferences of Hog Farmers

Figure 4.1 shows the results from the lottery for hog farmers' risk preferences. The histogram displays the switching values in the lottery, which informs on subjects' certainty equivalent (Dohmen et al., 2010). The results indicate many hog farmers started to switch to the safety payment at ¥300. Only 8 out of 46 hog farmers switched to the safety payment after ¥600. This number is lower than the average winning amount of playing the lottery, which is equal to ¥750. In fact, only one hog farmer out of 46 hog farmers switched to the safety payment when the amount was higher than ¥750. Hence, our findings show that most hog farmers we interviewed were risk averse, which is consistent with previous results from both laboratory experiments and field experiments (Jianjun et al., 2015; Liu, 2013).

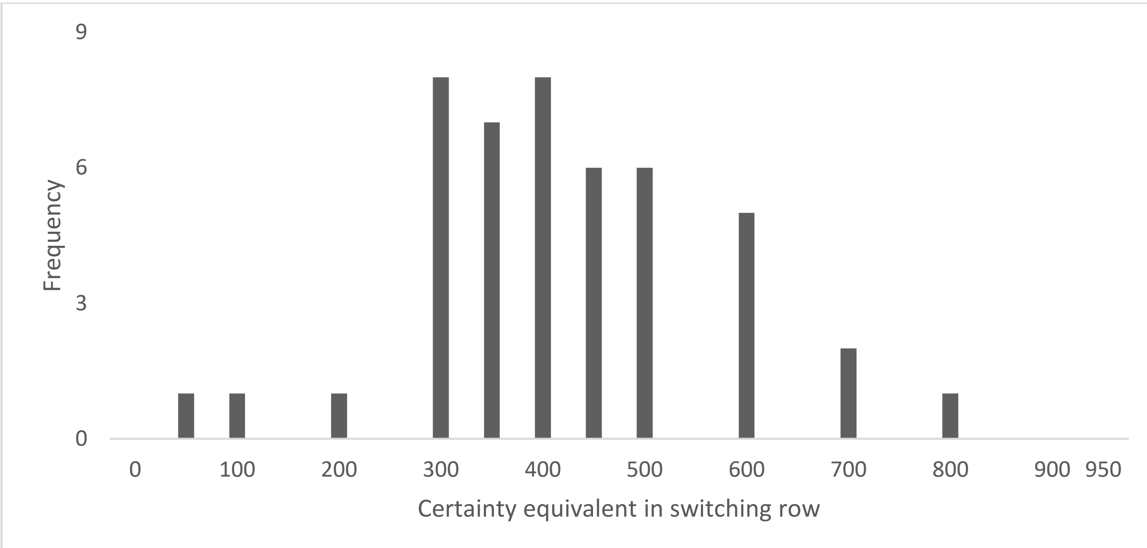
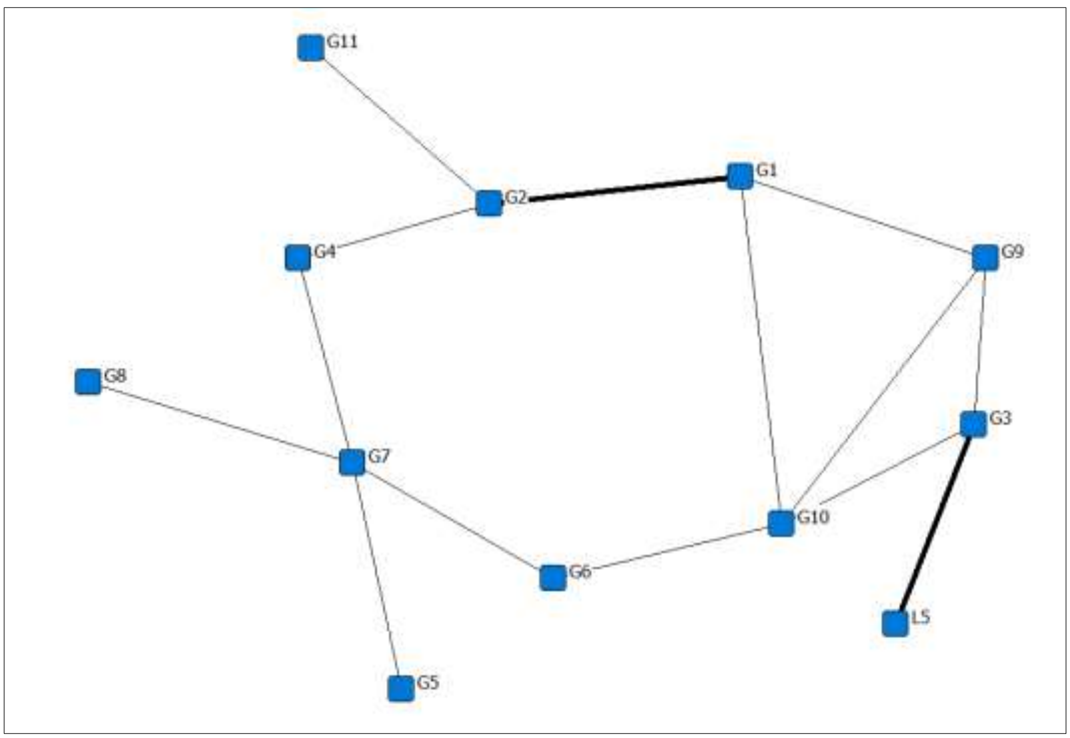


Figure 4.1. Risk Preference Results

4.4.5. Social Status, Power and Closeness among Hog Farmers

4.4.5.1. Core-Periphery Analysis

Next, we describe the social relationships of the hog farmers in all three locations determining their social status, power and how closely related they are to other farmers. This is then used to determine how peer effects influence the willingness to adopt genomics technology in the ordered probit model. The Core/Periphery analysis for hog farmers from all four different regions are shown in detail in Appendix G. Here, we display the social networks for hog farmers with regard to farmers with whom they discuss hog health issues. Figure 4.2 shows the network of County *G* in Chongqing (note, for confidentiality reasons we anonymized the names of counties). The weight of the line represents the strength of the connection between two actors. A thicker line represents the fact that both interviewees indicated each other as one of the top three farmers to discuss hog health with. In other words, a thick line indicates both actors mentioned each other while a thin line means that only one actor mentioned the other. For instance, G2 and G1 both mentioned each other as a main actor to discuss hog health with, but between G2 and G4 only one mentioned the other. Figure 2 indicates the relationships of G1 with G2, and of G3 with L5 are stronger than other relationships. Results from Figure 2 also indicate G7 and G10 not only have a high number of connections but are also connected to farmers who are linked to many other hog farmers.



Note: The thick lines indicate that both actors mentioned each other as important hog farmers to discuss hog health with (G2 to G1 and G3 to L5). Conversely, the remaining thin lines indicate that only one actor mentioned the other, e.g., between G2 and G4 only one mentioned the other. G1 to G11 and L5 indicate the 12 actors of the network in this particular location.

Figure 4.2. Social Network of Hog Farmers in G County

Figure 4.3 depicts the social network for hog farmers in County *L* in Chongqing. Again, the thickness of lines represents the closeness between actors. The thicker the line is, the stronger is the relationship between two persons. Figure 4.3 indicates hog farmers in *L* County are not well connected. Only G3, who is from another town has a strong relationship with L5. L1, L3, L5, L7 and L8 are five hog farmers in the core because of the stronger relationship between them when compared to others.

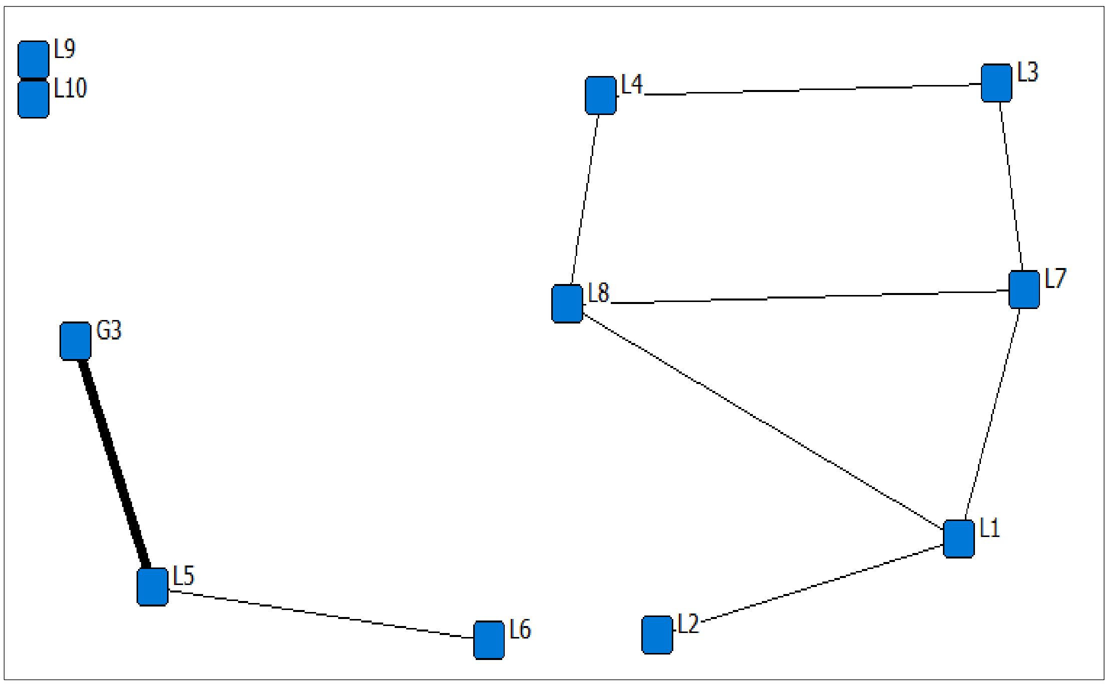


Figure 4.3. Social Network for Hog Farmers in L County

Figure 4.4 depicts the social network of hog farmers in County *S* in Chongqing. Hog farmers in S County are more connected compared to Counties *L* and *G*. There are also stronger relationships among hog farmers. For example, S6 has a close relationship with both S3 and S7, while S7 is also close to S4. In this case, it is not surprising that S3, S6, and S7 are in the core.

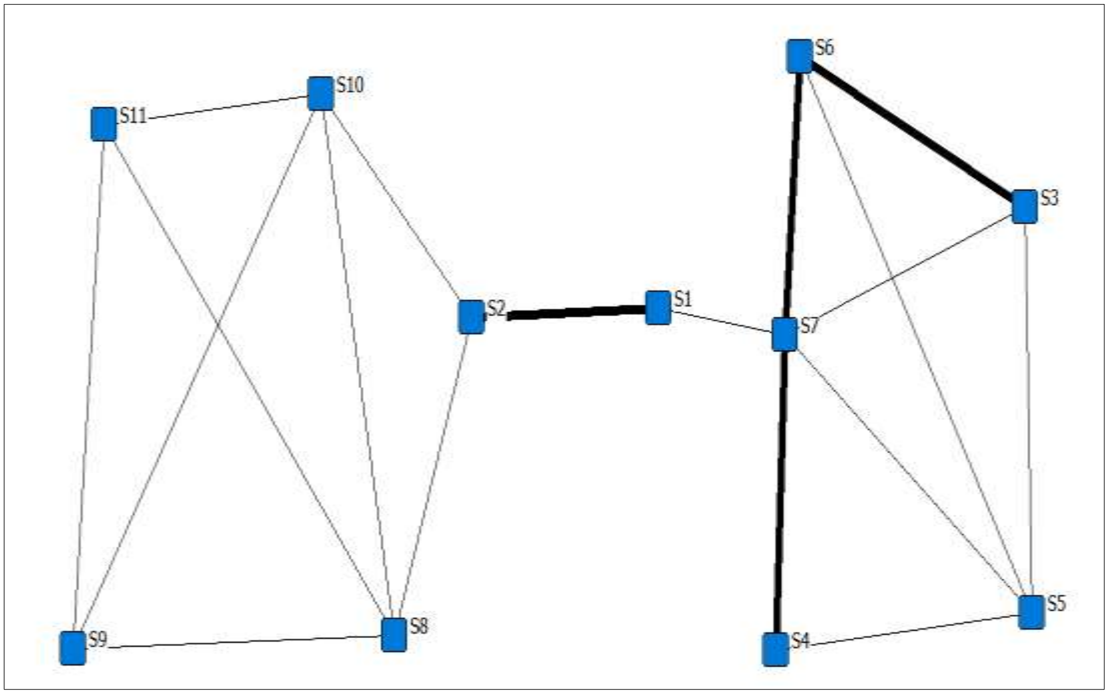


Figure 4.4. Social Network of Hog Farmers in S County

The social network for hog farmers in a village in Hebei province is shown in Figure 4.5. Unsurprisingly, hog farmers from the same village are more connected than those from different counties in Chongqing. Figure 5 also indicates that there is a strong relationship among H3, H4 and H6, and H12 is well connected with both H13 and H14. The strong relationships among H3, H4 and H6 lead them to be in the core while others are in the periphery.

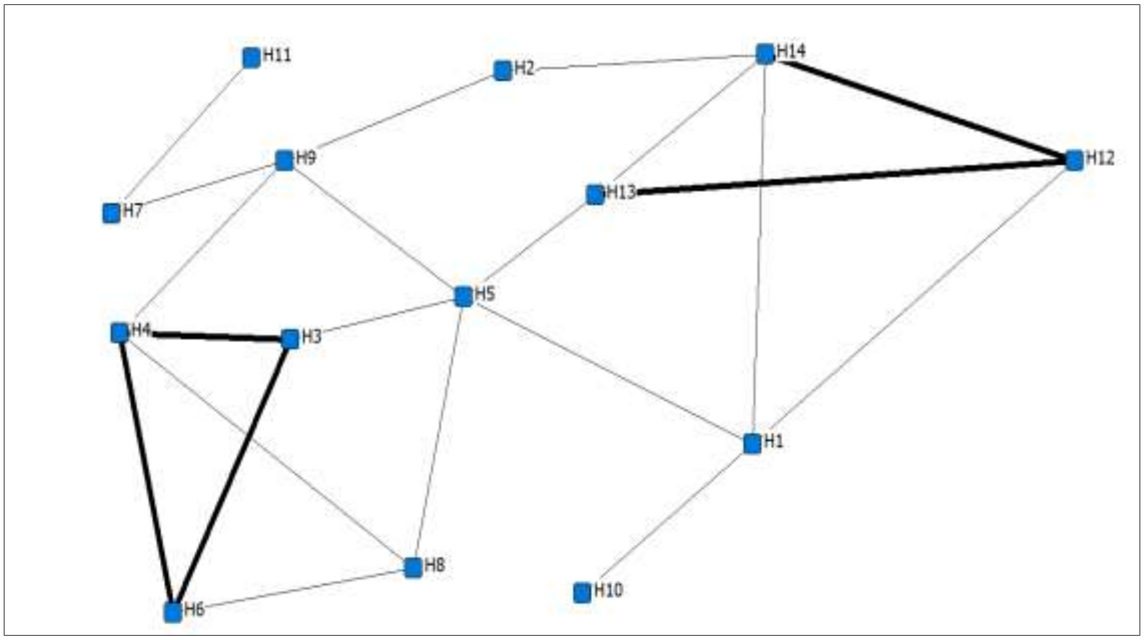


Figure 4.5. Social Network of Hog Farmers in a Village at Hebei Province

4.4.5.2. Centrality Measures for Chongqing and Hebei

Next, we discuss the centrality measures for hog farmers. Note, tables with details on the centrality measurement results for hog farmers in all counties are provided in Appendix H, I, J, and K. The centralities, no matter whether it is degree, closeness or betweenness centrality, are used to measure the importance of each actor in the social network with regard to information flow of hog health related information. We find that G7 and G10 have the highest Freeman's degree centrality, which means they have more connections than others. Interpreting results of normalized closeness centrality, a higher number means that one person is closer to other people, hence, being able to pass on or receive information. Results indicate G10, who has the highest normalized closeness centrality, is quite important in the network. On the other hand, not surprisingly, L4, a hog farmer from L County, is the least important person in this network. In terms of betweenness Centrality, G7 has the most power to pass on information in the network. This is consistent with the result from closeness centrality, given that betweenness centrality only measures use of the geodesic path.

The centrality results from *L* County are similar to the results from G County. Three hog farmers have the highest Freeman's degree, which means they have the largest number of connections. Results from both closeness centrality and betweenness centrality indicate that hog farmers with the largest closeness centrality are also the ones with the high betweenness centrality.

The centrality results for *S* County show that S7 is connected to 5 hog farmers directly among a total of 11 hog farmers. This is similar to the results from *L* county. The results of closeness and betweenness centralities illustrate that S7 and S1 are the two most powerful hog farmers in the network. Both of them are the most reachable farmers who will receive/pass on information to other hog farmers.

The centrality results for hog farmers in a village in Hebei province show that H5 has five direct connections among a total number of 14 hog farmers, which is the largest number of connections. On the other hand, H10 and H11 are two farmers who have the lowest Freeman's degree centrality. Results of closeness centrality and betweenness centrality show that H5, the one who has the highest number in Freeman's degree is also the most reachable and has the most power to activate this network. In contrast, H6 is relatively difficult to reach and needs more time to activate information flow in the network even though he has three direct connections. Surprisingly, H7, who has less direct connections than H4, has the larger degree of betweenness centrality, which means he could activate information flow in this network in the shortest amount of time.

4.4.5.3. Relationship between Social Networks and Willingness to Adopt Genomics Technology

Next, we test if the relationships among the farmers affect their willingness to adopt genomics technology. Previous literature has found that networks are formed along homophilous lines; that is, among people who are similar to each other (Jackson, 2008; Matuschke and Qaim, 2009). To test this hypothesis with regards to willingness to adopt genomics, we start by conducting differences-in-means tests for the willingness to adopt variables between hog farmers and their network partners.

To create the adoption variables for hog farmers' network partners, we first matched the names they indicated to discuss hog health with to the names of those who were also interviewed. Results indicate that for 42 out of 46 hog farmers we interviewed, we also interviewed at least one of the hog farmers they indicated to discuss hog health with. As Table 4.6 shows, for a large percentage of hog farmers in the three counties in Chongqing only one network member was interviewed, but in the village in Hebei province the number of network members interviewed increased to 2. Given that hog farmers in Hebei are all from the same village, they live closer together than farmers from Chongqing. Thus, this result is consistent with our expectation.

Table 4.6. Number of Network Members We Interviewed in Two Cities

Number of network members	Chongqing (%)	Hebei (%)
0	2 (6%)	2 (14%)
1	17 (53%)	4 (29%)
2	8 (25%)	7 (50%)
3	5 (16%)	1 (7%)
Total	32 (100%)	14 (100%)

Following Matuschke and Qaim (2009), we created the adoption variables of the network members equal to the sum of each network member obtained by dividing the number of network members we interviewed. The detailed results for the difference-in-means test for the adoption variables between hog farmers and their network members are also presented in Appendix L. In order to compare genomics technology adoption decisions, we chose answers for multiple genomics adoption related questions, (1) timeframe for adoption and (2) adoption based on different reduction rates of ASF. Results indicate there is no statistically significant difference among answers given by hog farmers themselves compared to the answers from their network members. This result confirms that hog farmers form their networks with farmers who are similar to them. However, one has to be cautious when interpreting this result because the fact that we find the farmers are not significantly different does not suggest that they are significantly more similar than others or influence each other. Also, while it is possible that a central actor is not more likely to adopt genomics, his behavior might influence peers close to him, whether he decides to adopt or not.

4.4.5.4. Relationship between Social Networks and Risk Preferences

Next, we also conducted a mean-difference test to evaluate whether network members have similar risk preferences. The results in Appendix L indicate there is no statistically significant difference for risk preferences among hog farmers compared to their network members. While this result confirms that hog farmers form their networks with farmers who are similar to them, the findings need to be interpreted cautiously keeping the arguments brought in the previous section in mind.

4.4.6. Hog Farmers' Willingness to Adopt Genomics Technology

4.4.6.1. Effect of Attitudes and Risk Preferences on Hog Farmers' Willingness to Adopt Genomics Technology

To test the relationship between attitudes, risk preferences, and willingness to adopt genomics rather sooner than later (or never), we estimated ordered probit models. Overall, the result from the likelihood ratio test is significant, which indicates that this model has satisfactory explanatory power. In addition to attitudes towards genomics and risk preferences, we included age, education, as well as, experience with hog farming in the model. The parameter estimates are presented in Table 4.7.

Risk preference, the factor that is associated with hog farmers' concerns about breeding with genomics technology, *City* and *Years of experience* variables are statistically significant in affecting the time hog farmers would take to adopt the technology. More specifically, the significant and positive *Risk preference* variable suggests that hog farmers who are less risk averse are more likely to adopt semen produced using genomics sooner. This result indicates that the more risk averse hog farmers are, the less likely they are to adopt the new technology quickly. The significant and negative *Years in experience* variable indicates that hog farmers who have raised hogs for a long time are more likely to adopt the genomics semen at a later point in time. Participants living in Chongqing are more likely to adopt the semen made using genomics in a shorter time frame. This result is consistent when we consider the fact that ASF had worse consequences for hog farmers in Chongqing compared to farmers in Hebei. The significant and positive *Factor 1_Breeding* variable indicates that hog farmers who consider the breeding effect of genomics as important are more likely to adopt the technology sooner. The other factors are insignificant, suggesting that hog farmers' attitudes towards resources and competitiveness do not significantly affect their genomics adoption decision.

Table 4.7. Effect of Risk Preference and Attitudes on Adoption of Genomics

Explanatory variable	Coefficient	Z-statistic
Factor1_Breeding	0.472*	1.84
Factor2_Resources	0.092	0.43
Factor3_Competitiveness	-0.164	-0.56
Risk preference	0.179***	2.41
Education	0.096	0.28
Years in experience	-0.063*	-1.85
City	1.010*	1.70
Log-likelihood	-49.026	
Likelihood ratio test	14.07***	
Pseudo R-squared	0.135	

Note: ***, **, * indicate significance at 1%. 5%, 10% level, respectively. N=44

4.4.6.2. Effect of Social Status, Power and Closeness on Hog Farmers' Willingness to adopt Genomics Technology

To test how hog farmers' social network status affects their willingness to adopt genomics sooner rather than later (or never), we model the effect of social network metrics on the willingness to adopt. The significant result for the likelihood ratio test indicates that the model has satisfactory explanatory power. The dependent variable indicates the timeframe within a given hog farmer would adopt genomics technology, ranging from never to immediately. We start by estimating separate ordered probit models including variables for centrality (degree, closeness, betweenness), core/periphery and other hog farmers' willingness to adopt genomics (see Table 4.8). We do not include a model with all three centralities given that they are highly correlated.[5,6]

Results in Models 1-3 show that neither degree, closeness, nor betweenness centrality significantly affect adoption. We also test whether those hog farmers who are in the core of a network would adopt genomics technology in a shorter timeframe. However, results in Model 4 show that the "core" variable is insignificant.

Next, we test whether the willingness to adopt of hog farmers in the social network of a given hog farmer will affect his willingness to adopt. The significant and positive results in Model 5 show a hog farmer's peers' adoption decisions are positively correlated with their own adoption decision. Results do show the sooner one's peers would adopt genomics, the more likely the hog farmer himself would adopt this technology in a shorter timeframe (given that the dependent variable indicated timeframe from immediately adopt to never adopt). However, one has to be cautious in interpreting this finding given that we interviewed only a few non-random members for each participant. Thus, based on the "friendship paradox" (on average, a hog farmer's 'friends' have more friends than he has (Feld, 1991)), these are seemingly more central than the average farmer and could therefore potentially have a stronger influence on others.

[5] The correlation coefficient between degree and closeness centrality is 0.6593, and the correlation coefficient between closeness and betweenness centrality is 0.6271. The correlation between degree and betweenness centrality is 0.5149.

[6] Closeness and betweenness centralities are normalized before entering the model.

Table 4.8. Social Network Effects on Adoption of Genomics

	Model 1	Model 2	Model 3	Model 4	Model 5
Degree	-0.173				
Closeness		-0.014			
Betweenness			-0.008		
Core				0.230	
SNA_adopt					0.860***
Log-likelihood	-62.197	-62.322	-62.654	-62.643	-51.697
LL test	1.57	1.58	1.50	0.60	9.72***
Pseudo R2	0.013	0.011	0.005	0.006	0.148
N	46	46	46	46	44

Note: ***, **, * indicate significance at 1%. 5%, 10% level, respectively.

4.4.7. Joint Effects of Farmer Characteristics and Network Effects on Technology Adoption

Table 4.9 reports models that combine farmer characteristics and network effects. Note, the variable "City" was excluded in the models including *SNA_adopt* because of high correlation (0.55633). The significant result for the likelihood ratio test indicates that all five models have satisfactory explanatory power. Findings are overall consistent with results presented in Tables 4.7 and 4.8, demonstrating the robustness of our analysis. Results indicate that neither degree, closeness, nor betweenness centrality; or whether farmers are in the core of a network affect their time frame for adopting genomics.

Model 6 in Table 4.9 is the most comprehensive model, hence, we will discuss these findings in detail. Risk preference is significant and negative, indicating that the riskier one's behavior, the more likely to adopt genomics technology rapidly. The more experienced the hog farmer, the more likely to adopt the new technology later. Hog farmers who consider the breeding effect of genomics technology as important are more likely to adopt genomics sooner. Hog farmers' willingness to adopt genomics is also affected by their peers' preferences in that the sooner their peers are to adopt it, the more likely they are to adopt more rapidly. However, as mentioned above, we interviewed non-random actors, hence, our findings might be biased by the "friendship paradox" (Feld, 1991).

Table 4.9. Effect of Social Networks, Risk Preferences and Attitudes on Adoption of Genomics

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Factor1_Breeding	0.553*	0.678**	0.527**	0.473*	0.537*	0.550*
Factor2_Resources	0.167	0.100	0.052	0.093	-0.209	-0.111
Factor3_Competitiveness	-0.141	-0.003	-0.078	-0.162	-0.276	-0.190
City	0.857	0.884	1.131*	1.010*		
Risk preference	0.158**	0.160**	0.138	0.179**	0.214***	0.180**
Education	0.019	0.112	0.152	0.096	-0.206	0.262
Years in experience	-0.055*	-0.067**	-0.063*	-0.063*	-0.069**	-0.060*
Degree	-0.270					-0.216
Closeness		-0.029				
Betweenness			-0.012			
Core				0.009		0.170
SNA_adopt					1.052**	0.957***
Log-likelihood	-47.767	-47.740	-48.501	-49.027	-42.637	-42.151
LL test	13.58***	16.70***	18.49***	14.09***	22.46***	28.19***
Pseudo R2	0.157	0.158	0.144	0.135	0.217	0.226

Note: ***, **, * indicate significance at 1%. 5%, 10% level, respectively. N=44

4.5. Discussion and Conclusion

The outbreak of ASF has had a substantial negative impact on the Chinese pork industry since 2018. Researchers around the world are trying to find a treatment for this disease and using genomics technology could provide a possible solution (Mazur-Panasiuk et al., 2019). In fact, genomics technology has been used before, e.g., in order to control the “Blue Ear Disease” in 2015. However, many Chinese people still hold negative views towards genomics. Previous literature finds that farmers’ risk preferences and their attitudes significantly impact their technology adoption decisions (Areal et al., 2012; Gillespie et al., 2004). In addition, there is abundant literature, which finds that social relationships have a significant impact on human behavior (Marsden & Friedkin, 1993, Granovetter, 1973). For instance, hog farmers who have strong ties with stakeholders will acquire new knowledge easier (Santos et al., 2021). Also, hog farmers in networks with more adopters might be more likely to adopt it themselves. Therefore, this paper attempted to understand hog producers’ willingness to adopt genomics to breed hogs that are more resistant towards diseases like ASF focusing on the effects of risk preferences, attitudes and social networks.

Exploratory results from 46 hog farmers from three counties in Chongqing and a village in Hebei province indicate most hog farmers we interviewed are highly risk averse and the semen created with genomics would need at least a 60% reduction in ASF infection in order to attract more adoption from hog farmers. Results from ordered probit models suggest hog farmers who are more risk averse and have more hog operation experience are more likely to adopt the semen at a later time. This finding is in line with Nie et al. (2021), who found that risk preferences of Chinese coastal farmers have a significant impact on farmers’ decisions related to technology adoption. Results from social network analysis indicate that hog farmers are closely connected. This result is consistent with findings from Santos et al. (2021), who found that networking among farmers in South Brazil is high, providing a favorable environment for information dissemination. Xia et al. (2020) also found the small-world phenomenon that farmers from the same village in southern parts of China are well connected. The high correlation between three centrality measures illustrates that the hog farmer who has the highest number of connections is always the one who is the most reachable. This result is supporting the findings from Wang et al. (2021), that households with more connections are easier to access resources and opportunities, which will improve their livelihood resilience.

This study also tested whether hog farmers are similar to their networks in adoption decisions with respect to genomics technology and whether they have similar risk preferences. The mean-difference test results indicate hog farmers' networks are formed along homophilous lines. There is no significant difference in results between the genomics adoption time frame of a particular hog farmer and the time frame from their peers. This indicates they not only have similar risk preferences, but also share similar attitudes towards adopting genomics technology. However, one has to be cautious when interpreting this result since an insignificant difference does not mean the hog farmer and their peers are being significantly more similar than other hog farmers they are not directly connected with. What we may observe is that central actors are not more likely to follow recommendations for genomics than others, however, the position they take has the potential to influence their acquaintances, independently of whether they are for or against adoption of genomics.

Results for all hog farmers' social status, power and centrality measures including degree, closeness, betweenness centrality and core-periphery in each model are insignificant indicating that hog farmers' positions in their social networks do not affect their time frame for genomics adoption significantly. However, findings show that the time frame that hog farmers prefer to adopt genomics is significantly and positively correlated with their peers' time frames regarding genomic technology adoption; but this result needs to be viewed with caution since we only interviewed one or two peers of each hog farmer and the peers we interviewed were not randomly included in the study.

To conclude, this study explored hog producers' willingness to adopt genomics to breed hogs that are more resistant towards ASF. Data were collected during the ASF outbreak in China, focusing on the effects of farmers' risk preferences, attitudes and social networks. Because of the difficulty in collecting data, the sample size is relatively small. Future research using large datasets from more places in China will be helpful in further determining hog farmers' motivations to adopt genomics technology. It might be fruitful to collect larger samples of social network data including participants randomly to further investigate preferences for technology adoption.

Reference:

Gao, S., C. Grebitus, and T.G. Schmitz. 2022. "Effects of Risk Preferences and Peer Influence on Adoption of Genomics by Chinese Hog Farmers." Journal of Rural Studies 94:111–127

CHAPTER 5

COMMUNICATION IN TIMES OF CRISES: INFORMATION FLOW AMONG CHINESE HOG PRODUCERS DURING THE AFRICAN SWINE FEVER OUTBREAK

5.1. Introduction

African Swine Fever (ASF) is a highly contagious and deadly viral disease affecting both, domestic and wild pigs of all ages (USDA, 2019). Pigs with a highly virulent strain of ASF typically experience high fever, decreased appetite, weakness, coughing, and difficulty breathing. ASF is often characterized by high morbidity and mortality rates, and most infected pigs die within ten days (Shao et al., 2018; USDA, 2020). Most importantly, there is no vaccine or treatment for ASF, yet. Hence, for hog producers it is a disaster if their hogs contract ASF.

The ASF virus was first identified in Kenya in the 1920s. It had an enormous economic impact on Europe's economy ever since it first appeared there, in the 1990s. In 2007, the virus returned to Africa and reached the East territory of the European Union in 2014, causing havoc in all European countries (Galindo and Alonso, 2017). For example, in Russia ASF killed more than 800,000 hogs between 2007 and 2017 (Kolbasov et al., 2018). In summer 2018, the ASF virus was identified in China and the Ministry of Agriculture and Rural Affairs of China (MARA) reported the first ASF case in Liaoning province. Ever since, ASF has tremendously affected China's hog industry. By May 2020, MARA recorded over 170 cases from 32 provinces. As a result, more than 1.2 million hogs were culled (Gong et al., 2020), leaving hog producers devastated.

Because hog producers' livelihood is at stake during an ASF epidemic, they are highly sensitive to any news about ASF, which provides an environment for information to spread. While in need of relevant information (e.g., how to proceed when a hog is infected) there is a risk of falling victim to what has lately been dubbed "fake news." Hog producers are vulnerable to misinformation circulated by market actors attempting to benefit from the crisis. For example, certain criminal gangs started spreading rumors about the virus to force producers to sell pigs below market price (Liu, 2019). Besides the intentional rumors, there is also fake news diffused among hog producers. For example, the ASF vaccine, which was reported as commercially available in May 2020 was proven to be fake and illegally produced (Reuters, 2020). Most importantly, it has been found that stories involving fake news are typically disseminated significantly farther, faster, deeper, and more broadly than the truth (Lazer et al. 2018; Vosoughi, Roy, and Aral 2018). At the same time, hog producers in China have taken different actions because of the disease outbreak. Some choose not to replenish herds while others continue to expand (Xu, 2019; Liu, 2019). Therefore, the spread of information can have serious consequences during an epidemic, which makes it necessary to understand how information flows in times of crisis.

Previous studies have shown the effect of social relationships on dissemination of information and behavioral characteristics (Marsden and Friedkin, 1993; Granovetter, 1973). For instance, if a hog producer is well-connected, e.g., with other hog producers and veterinarians, he is less likely to fall victim to a scam. Ghorbani et al. (2022) studied the trusting relationships of rural women involved in the local organization in Iran using social network analysis and found farmers have higher level of trust to other farmers if they are in the same organization compared to those who do not belong to their organization

(Ghorbani et al., 2022). Brehm et al. (2004) found people who share the same religion and have resided longer in a community will have a higher social attachment to the community. Previous literature has studied the benefits of increasing the efficiency of information flow, such as, increasing welfare. For example, Ramirez (2013) found social networks can enhance adoption of new technology by increasing the information flow and knowledge exchange between actors in the network. Jensen (2007) found the adoption of mobile phones by fisherman in India can reduce price dispersion and increase consumer market efficiency. Aker and Fafchamps (2015) found similar results on the producer side, where mobile phone adoption could reduce spatial producer price dispersion and increase producer welfare. In addition to the benefits of increasing information flow efficiency, previous studies have shown how information spreads among producers. For example, Jäckering, Gödecke and Wollni (2019) analyzed how information spreads in Kenya, mainly focusing on the flow of agricultural information and nutrition information, respectively. They found nutrition information is mainly exchanged within farmer groups to a more limited extent compared to the flow of agricultural information. Skaalsveen, Ingram and Urquhart (2020) studied the effect of information flow among producers in England on the implementation of no-till farming practices and found most producers said they preferred face to face meetings with others. However, internet platforms and social media like Twitter are crucial for communication among producers who live farther away from each other. In their studies on knowledge exchange regarding sustainable soil management for producers in the European Union, Mills et al. (2019) found that Twitter is efficient in spreading information; while Thompson (2021) concluded that local media are important for rural Americans to obtain local news and information in order to participate in local activities.

Building on these studies, findings from our research can also inform on how behavior has been changing during the pandemic of COVID-19. The information flow during ASF could be compared to the information flow during COVID-19. What are the methods individuals use to communicate with each other, and how often and with whom do they communicate and share information during a disease outbreak? The answers to these questions are important for stakeholders to know if they want to transmit correct information and control the spread of misinformation more effectively.

Hence, our objective is to analyze how information spreads during a time of crisis and aim to understand how social influence affects (hog farmer) behavior in the presence of a disease outbreak. The present study contributes to social relationships among producers and how information spreads during the outbreak. In a broader context, these findings could be transferred to any individual during a time of crisis.

How actors respond to information and how they share knowledge is important for stakeholders to know, so they can understand the flow of information, are able to transmit information efficiently, and can control spread of misinformation more effectively.

5.2. Methodological Background

5.2.1. Design of the Study

To test information flow during the ASF outbreak, we conducted a face-to-face survey in Chongqing, China in the summer of 2019. The survey was translated from English to Chinese by the research team before presenting it to the hog producers. Chongqing; one of four municipalities in China; is a big city located in southwestern China with more than 30 million citizens. Chongqing is well-known for both hog production and pork consumption. The data from National Bureau of Statistics of China (NBS) showed Chongqing ranking eleventh in hog production out of all provinces in China, with more than 17.58 million pigs bred in 2018. However, hog production per citizen is much greater than in the rest of the country. People in Chongqing prefer to eat pork. Chongqing citizens consume an average of 74 lbs of pork annually, ranking second out of all provinces, just behind the neighboring Sichuan province (Sina, 2019).

The outbreak of ASF had a massive effect on the hog industry in Chongqing. After the first ASF case in Chongqing was reported by MARA on Nov. 4th, 2018 a total of three ASF cases were reported in Chongqing. The first event occurred in Bishan, Chongqing, on December 18, 2018 and the third event happened in Shizhu, Chongqing, on March 21, 2019.

In addition to surveying hog producers in Chongqing, we also collected data from a village in the Hebei province. There are two main reasons to choose to survey hog producers from Hebei. First, according to MARA, the outbreak of ASF did not spread to Hebei province. Second, Hebei province is located in the northern part of China allowing for a comparison of the South and the North. Hebei is also famous for its hog production industry. The data from the Ministry of Agriculture (MOA) indicate that Hebei province ranked eighth place in hog production for all provinces in 2016 with more than 34.54 million hogs. However, different from the diet in Chongqing, the average pork consumption per capita in Hebei ranks only 22nd out of all 31 provinces in China (Sina, 2019). By comparing the results from Chongqing to Hebei, we aim to test how generalizable our results are, accounting for regional effects of information flow during the ASF outbreak.

We received a total of 65 completed surveys in the Chongqing district from three different counties and were left with 32 valid surveys for data analysis after eliminating 33 surveys that were filled out by neighboring producers and one survey from a farmer who earned less than 50% of their total income from raising hogs in 2018. We eliminated the small-scale farmer to be able to analyze information flow from more professional hog producers instead of from producers who only raise hogs to provide food for themselves. In addition, a total of 14 valid surveys were received from Hebei.

Collecting the data proved challenging given that individual hog farmers were concerned about meeting in person during the outbreak of the highly contiguous ASF. Hence, our sample size is relatively small. However, the overall sample size is comparable to other explorative, qualitative interviews, and expert interviews with sample sizes often being below 30 (e.g., see studies by Sonneville et al. (2009), Lachal et al. (2012), Bennet et al. (2013), Van Gilder and Abdi (2014), Takashi et al. (2016), Hunold et al. (2017), and Mitter et al. (2019), ranging from 12 to 21 participants). Second, our modeling relies on a panel structure which results in a higher number of observations.

5.2.2. Survey Instrument

As mentioned, the data used in this study were obtained using face-to-face interviews. The questionnaire contained demographic information including gender, age and education level, as well as hog farming's operating characteristics such as the type of hog farming (farrow to finish, farrow to feeder etc.), revenue and the costs associated with hog raising, including insurance and labor. The main part of the survey focused on the social networks relationship of hog producers related to the ASF outbreak. Hence, all questions regarding their relationships with others were phrased towards hog health. The rationale for this is that in times of crises, stakeholders need to disseminate information related to health/diseases. Therefore, we investigate the information flow related to hog health. The questions inform us as to how close the producers are to each other, and how often they connect with other hog producers, veterinarians, and sales agents to uncover the information flow among them as it relates to hog health.

To measure the closeness of the relationship with other hog producers, veterinarians, and sales agents, we first asked hog producers to think about other hog producers, veterinarians, and sales agents they always discuss hog health with and how close they are to them. Then, we asked them to list the top 3 names of other hog producers, veterinarians, and sales agents, respectively and to rate their relationships to them based on a Likert scale that indicated four relationship categories: 1=acquaintance, 2=friend/kinship, 3=good friend/kinship, or 4=close friend/kinship.

To operationalize information flow among hog producers and their hog farmer peers, veterinarians, and sales agents, we first divided their communication based on: (1) their communication modes; and (2) their periods of communications. The three communication modes included were social network text (We Chat, etc.); phone call/online calling (e.g., video chat), and in-person meetings. The two periods included were communication frequency before the ASF outbreak and after the ASF outbreak. We collected data on the communication frequency between hog producers and each stakeholder via the three communication modes, and before and after the ASF outbreak. Participants indicated their communication frequency on a Likert scale from 1 to 6 for each of the other actors (producers, veterinarians, sales agents), where 1=Less than monthly; 2=Monthly; 3=A few times a month; 4=Weekly; 5=A few times a week, and 6=Daily.

5.2.3. Random Effects Ordered Probit Model

In our study, we measure the flow of information among hog producers in terms of communication frequency for each interviewed hog farmer with other hog producers, veterinarians and sales agents. The corresponding question asked participants to indicate how often on average they were (before ASF) and are (now) in contact with their three most important individuals as it relates to hog health. We asked for three contacts each for producers, veterinarians and sales agents, and offered the aforementioned modes of communication. See Appendix M (Q8-Q9) for the survey instrument. There are a total of six answer categories (1) Less than monthly, (2) Monthly, (3) A few times a month, (4) Weekly, (5) A few times a week, and (6) Daily. Because only a few hog producers chose (6) Daily as the frequency to communicate with others, we combined (6) Daily with (5) A few times a week into “At least a few times a week”. Therefore, we have a total of five categories to indicate the communication patterns between each hog farmer with other actors.

In order to shed light on the information flow during a time of crisis we collected data on communication patterns for both, before and after ASF. Given the ordinal data structure, we use a random effects ordered probit model to estimate the effect of ASF on communication patterns among each hog farmer with other hog producers, veterinarians and sales agents. Different from the multinomial probit model, the ordered probit model accounts for the ordinal nature of the dependent variable, especially when the multinomial-choice variables are inherently ordered. For example, the dependent variable "difference in frequency of meeting with veterinarians before and after ASF" in our model is the difference of the Likert Scale numbers, which means the number is ordinal instead of cardinal. Similar to other probit models, the ordered probit model begins by assuming a linear functional form for a respondent's indirect utility function. The unobserved preference obtained by hog producer i to maintain the frequency in communication with other people before or after ASF is:

$$y_{it} = \beta x_{it} + \varepsilon_{it} \tag{1}$$

where x_i is the vector of independent variables including the identity of the person (hog farmer, veterinarian or sales agent); communication frequency before and after ASF, and location of hog farmer. β is a vector of coefficients associated with x_i, and ε_i is an error term assumed to follow a standard normal distribution. y_i is the observed ordinal variable, denoted as the frequency of communication with other people, which contains the following structure:

$$y_{it} = j \Leftrightarrow u_{j-1} < y_{it} \tag{2}$$

where j=0, …., M is the number of possible y outcomes where the highest category is M and u_j's are unknown cut-off values. In our case, M is equal to five. By assuming the error term ε_i to follow a standard normal distribution, the probabilities for y_i are

$$\Pr(y_{it} = 0) = \int_{-\infty}^{-\beta x_i} \phi(\varepsilon_{it}) d\varepsilon_{it} = \Phi(-\beta x_{it})$$

$$\Pr(y_{it} = 1) = \int_{-\beta x_i}^{u_1 - \beta x_i} \phi(\varepsilon_{it}) d\varepsilon_{it} = \Phi(u_1 - \beta x_{it}) - \Phi(-\beta x_{it})$$

$$\dots \dots \tag{3}$$

$$\Pr(y_{it} = M-1) = \int_{u_{M-2} - \beta x_i}^{u_{M-1} - \beta x_i} \phi(\varepsilon_{it}) d\varepsilon_{it} = \Phi(u_{M-1} - \beta x_{it}) - \Phi(u_{M-2} - \beta x_{it})$$

$$\Pr(y_{it} = M) = \int_{u_{M-1} - \beta x_i}^{u_M - \beta x_i} \phi(\varepsilon_{it}) d\varepsilon_{it} = \phi(u_M - \beta x_{it}) - \phi(u_{M-1} - \beta x_{it})$$

$$= 1 - \Phi(u_{M-1} - \beta x_{it})$$

where ϕ and Φ are the standard normal probability density and cumulative distribution functions, respectively.

Maximum likelihood estimation (MLE) was used to estimate the random effects ordered probit model. The log-likelihood function is

$$Ln\, \mathcal{L} = \textstyle\sum_{i=1}^{N} \sum_{j=0}^{M} Z_{ij} \ln[\Phi_{it,j} - \Phi_{it,j-1}] \tag{4}$$

where Z_{ij} is an indicator variable equal to 1 if $y_{it} = j$ and 0 otherwise.

5.2.3.1. How do hog producers communicate during a time of crisis?

To test if hog producers communicate more or less frequently with others after the outbreak of ASF, we estimate three models. The first model includes communication frequency before the crisis, the second model includes communication frequency after the ASF outbreak, and the third model includes all variables, as well as, a dummy variable to indicate “*After ASF Outbreak*” equal to 1 if the communication occurred after the outbreak. With these models, we test specifically whether hog producers’ frequency of *remote communication* (e.g., using text or social media) increased after the disease outbreak; and whether their frequency of *in-person communication* decreased after the disease outbreak. Given how contagious ASF is, we hypothesize that producers still communicate and transmit information, however, they might rather rely on socially distant means to do so.

5.2.3.2. Does geographic distance between hog producers lead to less frequent communication?

To test if greater geographic distance between hog *producers* and others reduces the communication frequency, we include a “Chongqing” dummy variable, which equals 1 if *producers* live in Chongqing and 0 if they live in Hebei. We also add an interaction term to indicate communication frequency after the outbreak in Chongqing: “*After_Chongqing*” in the full model to further test whether the geographic distance among hog *producers* has an effect on communication frequency after the disease outbreak.

5.2.3.3. How does closeness of relationships affect communication patterns?

To test if a closer relationship between hog *producers* and others makes a change in communication frequency less likely, we estimate a weighted model by adding information regarding the closeness of the relationship with other hog *producers*, veterinarians, and sales agents. To measure this, hog *producers* were evaluated on a Likert scale that ranged from 1 to 4 whether the other actors (producers, veterinarians, sales agents) are an “Acquaintance”; a ”Friend or kin”; a “Good friend”; or a “Close friend” (Marsden and Campbell, 1984). In the weighted model, we weigh all connections between the actors with the weights from the Likert scale. For instance, a relationship to a close friend is now coded

"4" instead of "1" and a friend is coded "2" instead of "1". Table 5.1 summarizes all variables used in the subsequent analysis.

Table 5.1. Summary of Variables Used in the Analysis

Variable	Variable definition
Chongqing	Dummy variable equal to 1 if the communication is measured for hog producers in Chongqing, 0 if it was measured for hog producers in Hebei.
Producer 1/2/3	Unweighted model: Dummy variable equal to 1 if the respondent communicated with hog producer 1/2/3, 0 if there was no communication. Weighted model: Categorical variable equal to 0, 1, 2, 3 or 4 if there was communication between the respondent and hog producer 1/2/3 and they are not connected (0), "Acquaintances" (1), "Friend or kin" (2), "Good friend" (3), "Close friend" (4).
Vet 1/2/3	Unweighted model: Dummy variable equal to 1 if the respondent communicated with veterinarian 1/2/3, 0 if there was no communication. Weighted model: Categorical variable equal to 0, 1, 2, 3 or 4 if there was communication between the respondent and veterinarian 1/2/3 and they are not connected (0), "Acquaintances" (1), "Friend or kin" (2), "Good friend" (3), "Close friend" (4).
Sales 1/2/3	Unweighted model: Dummy variable equal to 1 if the respondent communicated with sales agent 1/2/3, 0 if there was no communication. Weighted model: Categorical variable equal to 0, 1, 2, 3 or 4 if there was communication between the respondent and sales agent 1/2/3 and they are not connected (0), "Acquaintances" (1), "Friend or kin" (2), "Good friend" (3), "Close friend" (4).
Text	Dummy variable equal to 1 if the communication frequency is measured for using text, 0 otherwise.
Phone	Dummy variable equal to 1 if the communication frequency is measured for using phone, 0 otherwise.
After	Dummy variable equal to 1 if the communication is measured after the ASF outbreak, 0 otherwise.
After_Chongqing	Dummy variable equal to 1 if the communication frequency is measured for hog producers in Chongqing after the ASF outbreak, 0 otherwise.

5.3. Results

5.3.1. Sample Characteristics

The summary statistics of both demographic and hog operation information for hog *producers* from Chongqing and Hebei are presented in Table 5.2. 75% of hog *producers* in Chongqing manage the pigs for the duration of growth and development (farrow to finish), 7 out of 32 focus only on the feeder process, one hog producer operates with hogs from farrow to wean. All 14 hog producers in Hebei province manage pigs from farrow to finish, which means they manage the pigs for both growth and development durations. Most hog producers in both regions are male and less educated, and more than 40 years old. They have been raising hogs on average for more than ten years. Differences between the cities are, e.g., the variation in total revenue from hog operations which is higher in Chongqing compared to Hebei. A result that could be supported by the huge variation in hog mortality rates.

Table 5.2. Summary Statistics from Chongqing and Hebei

	N	Mean	SD	Min	Max
Hog producers from Chongqing					
Operation type	32	1.47	0.84	1	3
Education level	32	2.03	0.60	1	4
Age in years	32	48.81	6.74	37	65
Gender (male)	32	99%	0.18	0	1
Experienced in year	32	12.09	6.99	2	30
Total revenue in 10,000 RMB per year*	32	37.91	61.20	4	280
Hog producers from Hebei					
Operation type	14	1	0	1	1
Education level	14	2.36	.84	1	4
Age	14	46.14	6.41	37	56
Gender (male)	14	100%	0	0	1
Experienced in years	14	10.57	3.96	5	20
Total revenue in 10,000 RMB per year*	14	8.36	3.69	3	15

Note: * Total revenue is obtained after subtracting operation costs and adding income from other sources.

5.3.2. Impact of ASF on Information Flow

This study mainly focusses on information flow before and after ASF testing different information channels, such as, in person, text, or call. We test this for social networks of hog producers who are important to the interviewee with regards to hog health, namely, the interviewed hog producer's networks of other hog producers, veterinarians, and sales agents.

5.3.2.1. Information flow in Chongqing

Estimates of the impact of ASF on information flow with other hog producers, veterinarians and sales persons in Chongqing are provided in Table 5.3. Results show that before the ASF outbreak, hog producers always preferred to communicate with other hog producers and veterinarians in-person to discuss hog health. After ASF occurred, hog producers tended to connect with other hog producers and sales agents through text or phone while in-person communications were reduced. These findings are statistically significant, as indicated by a paired t-test. Our findings indicate that an epidemic with highly transmissible viruses like ASF significantly diminishes quality and quantity of information transmitted given producers are now abstaining from meeting other hog producers and salespersons. Previous literature indicates that meeting in person is more efficient than phone calls, and that phone calls are more efficient in passing information than texting (Kumar and Epley, 2020; Roghanizad and Bohns, 2017; Sadikaj and Moskowitz, 2018). This would suggest that less information is transmitted which could hinder less efficient treatment. Results match previous research which indicate that hog producers always met with other hog producers in person before the spread of ASF (Fei, 1947). Ultimately, the spread of ASF significantly decreases the amount of time spent with others, most likely because they were afraid that the in-person meetings could transmit the virus to their hogs. The results might indicate a barrier to efficiently disseminate important information.

That said, the rate of in-person meetings with veterinarians did not decrease after the first ASF case was reported in Chongqing, and one could argue that veterinarians offer more information on hog health than fellow producers. This is indeed different from the behavior among hog producers and sales agents. The increase in connections with veterinarians through phone calls and text match expectations, since hog producers may pay more attention to their hogs' health after the spread of ASF, which could lead to an increase in soliciting advice from veterinarians. Nevertheless, the stable frequency in meeting with veterinarians in person is partially an unexpected result, given that one could hypothesized that in-person communication would decrease if hog producers were worried about meeting with other people who may bring the virus to their hogs, especially since some veterinarians also manage their own hog operation and might be exposed to ASF. However, due to the ASF outbreak, producers could have the need for more suggestions from veterinarians when pigs are unwell. The stable frequency in meeting with veterinarians indicates the concerns associated with in-person meetings is canceled out by the demand associated with needing more help from veterinarians.

Table 5.3. Impact of the ASF on Communication Patterns in Chongqing

	No. of producers	Before	After	Difference
Communication between hog producers				
Text	32	3.75	4.16	0.41*** (0.06)
Phone	32	2.85	3.20	0.34*** (0.07)
Meet	32	2.21	1.16	-1.05*** (0.12)
Communication with veterinarians				
Text	28	1.96	2.12	0.17*** (0.04)
Phone	28	1.57	1.77	0.20*** (0.04)
Meet	28	1.42	1.42	0 (0.10)
Communication with sales agents				
Text	26	1.68	1.85	0.17*** (0.05)
Phone	26	1.47	1.49	0.13 (0.08)
Meet	26	0.90	0.63	-0.27*** (0.06)

Note: $***$ indicates significance at 1% level.

5.3.2.2. Information flow in Hebei

The results of ASF on information flow between hog producers, veterinarians and salespersons for a village from Hebei province are provided in Table 5.4. Similar to the results from Chongqing, hog producers preferred to connect with other hog producers, veterinarians, and salespersons in person before ASF. However, the outbreak of ASF decreased the frequency of in-person meetings, but increased the frequency of text and phone communication. The paired t-test results also indicate these differences are significant.

Comparing the findings for Hebei to the results from Chongqing, hog producers from the same village tended to meet more frequently with each other than producers from the same county before the outbreak of ASF. However, they were also more cautious about meeting with other hog producers in person after the ASF outbreak. This caused in-person meetings to decrease from several times a week to less than monthly for hog producers who live in the same village. Findings also indicate a significant decrease in meetings with veterinarians. One potential explanation for this finding is the impact of geographic location among hog producers. Hog producers in Hebei live closer together than producers in Chongqing, because they are all exposed to other hog producers. Almost all hog producers in the same village will instantly know if one of them has a veterinarian visiting. This could possibly lead other hog producers to reduce visits/ communication with the hog producer who had the veterinarian visiting. As a result, when adding more rigorous restrictions on the geographic location of hog producers by observing findings for actors from the same county to actors from the same village, we find that in-person communication with other hog producers and veterinarians may decrease more sharply during an epidemic due to potential pressure from other hog producers who live close by.

Overall, hog producers were more likely to connect more often with other hog producers, veterinarians, and sales agents after ASF spread. In some instances, the mode of communication changed. For example, the frequency of communicating with other hog producers and veterinarians through phone calls showed a significant increase. The frequency of meetings with other hog producers and sales agents in person after ASF spread declined. The closer hog producers are to each other, the more the frequency of in-person meetings with other hog producers and sales agents decreased. Hog producers in the same village in Hebei province also showed a decline in the frequency of meeting with veterinarians. Interestingly, hog producers in Chongqing remain at the same frequency of meeting with veterinarians in person after the spread of ASF, which means the negative effects associated with in-person meetings is canceled out by the positive impact associated with needing more help from veterinarians.

Table 5.4. Impact of the ASF on Communication Patterns in Hebei

	No. of producers	Before	After	Difference
Communication between hog producers				
Text	14	3.98	4.29	0.31** (0.14)
Phone	14	3.23	3.64	0.40** (0.17)
Meet	14	4.36	1.00	-3.36*** (0.25)
Communication with veterinarians				
Text	14	1.24	1.42	0.19*** (0.07)
Phone	14	1.14	1.21	0.07 (0.05)
Meet	14	1.05	0.62	-0.43*** (0.04)
Communication with sales agents				
Text	14	1.12	1.21	0.10** (0.04)
Phone	14	0.93	1.02	0.10** (0.04)
Meet	14	0.83	0.52	-0.31*** (0.04)

Note: ∗∗∗ indicates significance at 1% level.

5.3.3. Explaining Communication Patterns during the African Swine Fever Epidemic

Next, we estimate random effects ordered probit models. Our dependent variable is the frequency of communication, with the resulting distribution presented in Table 5.5. There are a total of 1,674 observations, adding up all instances between each participant and their closest three actors: other hog producers, veterinarians and sales agents, communicating by text, phone, or meeting in person. We find that more than 60% of the communication is less than or equal to a few times a month even after we combined "A few times a week" with "Daily" into "At least a few times a week", which means our communication frequency variable is highly skewed to the left.

Table 5.5. Frequency Distribution of the Communication Patterns Frequency

Frequency description	Frequency	Percentage
Less than monthly (1)	358	21.27%
Monthly (2)	416	24.97%
A few times a month (3)	460	27.48%
Weekly (4)	286	17.08%
At least a few times a week (5)	154	9.20%
Total	1,674	

The parameter estimates are displayed in Table 5.6. The first three columns contain the results of models with an unweighted dependent variable. As explained above, we estimate a series of random effects ordered probit models, both unweighted and weighted, for closeness of the relationship. The "Before" model tests effects on communication frequency before the ASF outbreak. The "After" model tests effects on communication frequency after the ASF outbreak. The "Full" model includes all variables adding two dummy variables. The variable "after" is equal to 1 if the communication is measured after the ASF outbreak. The variable "after_chongqing" is a dummy variable equal 1 if the communication frequency is measured for hog producers in Chongqing after the ASF outbreak.

Results for the weighted and unweighted models show that most coefficients are similar in terms of sign and magnitude. However, there are distinct differences for communication with sales agents in that hog producers are more likely to maintain the communication frequency with sales agents by adding information regarding the closeness of the relationship. This result shows that the closer the relationship among hog producers with other people, the lower the change in communication frequency, i.e., flow of information.

The results from the weighted and the unweighted models show that hog producers are more likely to communicate more with other hog producers, veterinarians, and sales agents, especially through text or phone call. The significant and negative "After" variable in both the weighted and the unweighted full models, suggests that hog producers are less likely to communicate with others after the outbreak of ASF. The significant and positive "Text" and "Phone" variables in both the weighted and the unweighted full models suggest that hog producers are more likely to communicate with others through remote communication modes like text or phone after the disease outbreak. These results indicate that hog producers' frequency of in-person communication with others decreases and remote communication increases after the disease outbreak, which can have implications for transmitting information.

Moreover, the unweighted and weighted models indicate that hog producers in Chongqing are more likely to continue to communicate as before with others compared to hog producers in the Hebei province. At the same time, results from the weighted models suggest hog producers in Hebei were more likely to communicate with others before the crisis, and the frequency decreased dramatically after the disease outbreak. This result is also identified in the “Full” model using the unweighted dataset. This result confirms our descriptive analysis and indicates that the greater the geographic distance of hog producers to others, the lower the communication frequency. However, the frequency is more likely to decrease if they live closer to each other.

Table 5.6. Random Effects Ordered Probit Model Results

	Not weighted by the relationship			Weighted by the relationship		
	Before	After	Full	Before	After	Full
Chongqing	-0.13	0.50***	-0.14	-0.43**	0.30*	-0.36**
	(-0.59)	(2.67)	(-0.73)	(-2.19)	(1.85)	(-2.23)
Producer1	1.94***	1.63***	1.53***	0.94***	0.64***	0.68***
	(5.16)	(3.96)	(5.69)	(11.76)	(8.02)	(12.25)
Producer2	1.97***	1.79***	1.62***	0.95***	0.68***	0.71***
	(5.25)	(4.35)	(6.00)	(11.96)	(8.63)	(12.78)
Producer3	1.78***	1.55***	1.43***	0.92***	0.64***	0.67***
	(4.74)	(3.78)	(5.31)	(11.32)	(7.83)	(11.85)
Vet1	0.88**	1.17***	0.86***	0.80***	0.65***	0.62***
	(2.35)	(2.86)	(3.19)	(8.21)	(6.62)	(9.01)
Vet2	0.64*	1.10***	0.71***	0.76***	0.66***	0.60***
	(1.69)	(2.64)	(2.58)	(7.44)	(6.49)	(8.37)
Vet3	1.14**	1.70***	1.17***	0.86***	0.79***	0.70***
	(2.47)	(3.41)	(3.53)	(7.20)	(6.57)	(8.33)
Sales1	0.38	0.41	0.33	0.79***	0.44***	0.54***
	(1.01)	(0.99)	(1.21)	(6.04)	(3.31)	(5.78)
Sales2	0.33	0.34	0.27	0.74***	0.41***	0.50***
	(0.85)	(0.81)	(0.97)	(5.57)	(2.99)	(5.26)
Sales3	0.00	0.00	0.00	0.43**	0.12	0.23
	(.)	(.)	(.)	(2.11)	(0.54)	(1.59)
Text	1.43***	3.36***	2.13***	1.49***	3.47***	2.19***
	(14.06)	(23.61)	(27.47)	(14.47)	(23.76)	(27.86)
Phone	0.58***	2.55***	1.37***	0.61***	2.63***	1.41***
	(6.07)	(19.51)	(18.99)	(6.25)	(19.75)	(19.34)
After			-0.64***			-0.65***
			(-6.54)			(-6.64)
After_chongqing			0.56***			0.58***
			(4.81)			(4.91)
Sigma2_u	0.44***	0.26***	0.29***	0.30***	0.15***	0.19***
	(3.98)	(3.47)	(4.17)	(3.75)	(2.97)	(3.94)
LL value	-968.36	-871.42	-2003.58	-930.00	-845.94	-1958.61

Note: *** indicates significance at 1% level.

5.4. Discussion and Conclusion

Since 2018, the outbreak of ASF has had a massive impact on the Chinese pork industry with more than 1.2 million hogs culled in China. Hog producers are affected most by this disease and are extremely sensitive to information regarding ASF (Liu, 2019). The question is how the epidemic has changed their modus operandi with regards to information flow. There is much literature that finds that social relationships have a significant impact on human behaviors (Marsden and Friedkin, 1993; Granovetter, 1973). This paper analyzes how information flows during an outbreak (epidemic). The results show with whom and through which communication channel hog producers choose to discuss hog health with. Local governments could use these results to disseminate important information to hog producers and avoid the spread of rumor and false information in an effective and efficient way.

A comparison of communication patterns before and after the ASF outbreak indicates that once the outbreak occurred, producers more often connected with other producers through text or phone calls and that in-person meetings were significantly reduced among hog producers, and among hog producers and sales agents. This general result has several implications. First, producers act responsibly when trying to reduce the spread of disease. Second, especially in a confined geographic area like a village, social interactions that played an important role in people's lives have been curbed. Third, even though producers are careful with in-person meetings and have switched their mode of communication to remote means, they still meet in-person if they deem it necessary for the health of their hogs. This was illustrated by the results of communication patterns with veterinarians for Chongqing. However, this behavior differed for hog producers from Chongqing compared to those who live in the same village in Hebei. The unchanged frequency of meeting in person with veterinarians for hog producers in Chongqing may suggest that panic associated with the "meet in person" effect is canceled out by the willingness to ask for help from veterinarians related to hogs that might be sick. On the other hand, the closer geographic distance among hog producers may bring increased social pressure to hog producers in Hebei to meet with veterinarians, which might have reduced in-person meetings with veterinarians significantly. These findings could be used to simulate contagion during an epidemic or a pandemic where it would be likely to witness similar behavior. Finally, information transfer might not be as effective via text/phone compared to in-person communication, which could be an indicator of ineffective information flow.

Results from the ordered probit model also suggest that hog producers are more likely to transmit information via text and phone, especially after the disease outbreak. Comparing the results from Chongqing and Hebei, the closer the producers live together, the more frequently they communicate with others and the frequency is more likely to decrease after the disease outbreak.

To summarize, this study explored how an infectious disease outbreak affects the spread of information by analyzing hog producers' communication patterns before and after the African Swine Fever outbreak in China. Because of the difficulty in collecting data, the sample size is relatively small. Future studies using large datasets from more regions in China could help to further analyze social networks and related information flow. Also, future research could conduct similar studies in other countries to test whether communication patterns are comparable. Another fruitful avenue might be researching producers other than hog producers. It would be interesting to test whether social networks and information flow are similar or different. Finally, given the current COVID-19 outbreak it would be of interest whether information flow and communication patterns among producers are comparable to the general public, especially given the increased risk of contagion during in-person gatherings.

CHAPTER 6

CONCLUSIONS AND IMPLICATIONS

The livestock supply chain has a significant impact on the global food system. It contributes 40% of the global value of agricultural output and provides livelihoods and food to almost 1.3 billion people (World Bank, 2022). Decision-making is a core issue in the livestock supply chain for both producers and consumers.

Modeling how producers and consumers make their choices requires a sufficient understanding of the process of their decision-making behavior. For example, previous literature has shown that depending on the processing resources, consumers' choices could be affected by affective processes, cognitive processes, or both affective and cognitive processes simultaneously (Grebitus and Van Loo, 2022). Hence, applying experimental methods, my dissertation investigated how producers and consumers make their choices. In particular, this dissertation focused on analyzing the effect of the attributes of the product, and the characteristics of the decision-maker on producers' and consumers' decision-making. Product attributes, such as, quality grades, country-of-origin, and organic labeling cand affect consumers' food choices through cognitive process. On the other hand, the characteristics of the decision-maker, including risk preferences and ethnocentrism can affect consumers' and producers' decision making through affective processes. I investigated this in my dissertation through four essays.

In the first essay, I evaluated consumer preferences for beef quality grading and how the quality grades impact consumers' willingness to pay for both domestic and imported beef. I found that consumers were willing to pay a premium for beef flank carrying a Premium quality grade compared to beef without quality grade information.

However, Regular quality beef received a negative WTP compared to ungraded beef. Results also show that imported beef could receive a higher WTP if it carries the Premium quality grade. However, consumers discounted imported beef in general. I concluded that the negative WTP for the Regular quality grade could be explained by three possible reasons: (1) consumers have negative associations with the word "Regular"; (2) consumers perceive ungraded beef as beef with a mixed quality; and (3) the beef grading system grades beef based on external sensory information, which consumers can easily identify. Hence, it can lower their WTP for quality grades, especially the Regular quality grade. Results from the first essay illustrate how product attributes, such as, quality grades, affect consumers' food choices.

By focusing on the impact of consumers' characteristics on their food choices, the second essay investigated Chinese consumers' ethnocentrism levels, their perceptions of major beef exporting countries and their perceptions of beef products from associated countries, as well as, to evaluate how this affects their preferences and WTP for beef from different countries. I found that Chinese consumers were ethnocentric and very much in favor of their home country. In addition, consumers from China were more likely to pay a premium for Chinese beef and discount foreign beef, such as, beef from the US and Australia, if they had a high level of purchasing incentives for Chinese products. Results also show that consumers increase their willingness to pay for foreign beef if they favor the country or the product image associated with that country. Hence, the results of the second essay demonstrated the importance of consumers' characteristics, such as, their ethnocentric levels, country image and product image, with regards to food choices.

To study how characteristics of producers affect their decision-making, the third essay focused on analyzing how farmers' risk preferences, attitudes, and social networks affect their motivations in adopting genomics technology during the outbreak of African Swine Fever. I found that most hog producers were highly risk averse. In addition, hog farmers who were more risk-averse and had more experience in raising hogs were more likely to delay the adoption of African Swine Fever-resistant semen as compared to more risk-prone farmers. Moreover, results from social network analysis showed that hog farmers were closely connected. Also, the genomics adoption time frame of a particular hog farmer was positively correlated with other closely related hog farmers' time frames, although hog producers' social network status, such as centrality, does not affect the time frame in which they would adopt genomics technology. This chapter identified the effect of producers' characteristics on their decision-making in the livestock supply chain.

In the last essay, I examined the impact of social influence on hog producers' behavior using social network analysis. In particular, I studied how information flows during an epidemic, such as, African Swine Fever. I found that hog producers made use of phones or texting more frequently to communicate during the African Swine Fever outbreak, while the frequency of face-to-face meetings with other hog producers and sales agents dropped. However, hog producers keep the same frequency of face-to-face meetings with veterinarians. Moreover, I concluded that geographic distance affected communication frequency significantly. In particular, the smaller the geographic distance of hog producers to others, the higher the communication frequency before African Swine Fever. However, the frequency was more likely to decrease after the African Swine Fever outbreak if they lived closer to each other.

The core findings of this dissertation provide insights that have widespread managerial and policy implications. First, because I found that consumers are willing to pay a premium for beef carrying a Premium quality grade and discounted beef with a Regular quality grade compared to ungraded beef, my findings indicate that government could achieve its goals in promoting the production of high-quality beef by releasing the tested beef quality grade system to the public. However, the system could bring some potential problems if a large percentage of beef would not be graded as Premium.

Second, by studying the effect of consumers' characteristics on their food choices, I found that consumers' ethnocentrism level, country image, and product image significantly affect their willingness to pay for domestic and imported beef. Therefore, domestic beef retailers could promote beef sales by advertising using the positive country image, and beef exporters could strengthen their beef exports to China by emphasizing the positive country or product images associated with their country.

Third, I found that most hog producers were risk averse, and their risk preferences would affect their technology adoption decisions. Over time though, most hog producers would be likely to adopt genomics technology considering the huge loss of hogs due to African Swine Fever. The government could use these results to efficiently promote new technologies, especially genomics. I also found that hog farmers were closely-connected, especially with likeminded producers. Government could use these results to activate hog producers' networks and disseminate important information effectively and efficiently.

Lastly, my findings on communication patterns and information flow during outbreaks provides implications for the government in disseminating important information to hog producers and avoiding the spread of rumors and false information in an efficiently. In particular, I concluded that the frequency of communication between hog producers with other producers and sales agents through phone and text increased significantly after the African Swine Fever outbreak, which suggests that government could make use of those communication modes, e.g., using text to disseminate information. Furthermore, I found that the frequency of meeting in-person with veterinarians remained the same after the outbreak, which suggests that government could distribute information to hog producers through veterinarians after the African Swine Fever outbreak.

However, each chapter of my dissertation is not without limitations. In the first essay, while I studied consumers' preferences for beef flank, further studies could analyze willingness to pay for Chinese beef quality grades using other beef cuts, such as steak. Also, I collected data in three major cities, but collecting data from other regions could be helpful in further exploring consumers' preferences for novel beef quality grades and the effects of quality grades on demand for imported beef. In the second essay, further research may want to explore consumers' country images and product images in more detail using other methods, such as, the affinity survey instrument which could be applied to measure consumers' country images. In the third essay, I used a relatively small sample. Future research may collect larger datasets, which could be fruitful in further determining hog farmers' motivations to adopt genomics technology. It would be helpful to collect larger samples of social network data including participants randomly to further investigate preferences for technology adoption. In the last essay, it would be interesting to test whether information flow and communication patterns among hog producers are comparable to other producers in the livestock supply chain.

REFERENCES

Abidoye, B.O., H. Bulut, J.D. Lawrence, B. Mennecke, and A.M. Townsend, 2011. US Consumers' Valuation of Quality Attributes in Beef Products. Journal of Agricultural and Applied Economics 43(1):1–12.

Ajzen, I., 1985. From intentions to actions: a theory of planned behaviour. In: Kuhle, J., Bechmann, J. (Eds.), Action Control: From Cognitions to Behaviors. Springer, New York, pp. 11–39.

Aker, J.C., Fafchamps, M. 2015. Mobile phone coverage and producer markets: Evidence fromwest Africa. World Bank Economic Review 29(2):262–292.

Alba, R. D., Kadushin, C., 1976. The intersection of social circles: A new measure of social proximity in networks. Sociological Methods and Research, 5, 77-102.

Areal, F.J., Riesgo, L., Gómez-Barbero, M., Rodríguez-Cerezo, E., 2012. Consequences of a coexistence policy on the adoption of GMHT crops in the European Union. Food Policy, 37, 401–411.

Balcombe, K., D. Bradley, I. Fraser, and M. Hussein, 2016. Consumer preferences regarding country of origin for multiple meat products. Food Policy 64:49–62.

Balogh, P., D. Békési, M. Gorton, J. Popp, and P. Lengyel, 2016. Consumer willingness to pay for traditional food products. Food Policy 61:176–184.

Bandiera, O., Rasul, I., 2006. Social Networks and Technology Adoption in Northern Mozambique. Economic Journal, 116, 869-902.

Barham, B.L., Chavas, J.P., Fitz, D., Ríos-Salas, V., Schechter, L., 2015. Risk, learning, and technology adoption. Agricultural Economics (Czech Republic), 46, 11–24.

Beef Magazine, 2021. Beef: Growing Demand in China. https://www.beefmagazine.com/beef/beef-growing-demand-china

Beijing Municipal Price Supervision Center (BMPSC), 2021. http://www.beijingprice.cn/jfcx/sp/index.shtml?ItemCode=E001507.

Belsley, D.A. A Guide to Using the Collinearity Diagnostics.Computer Science in Economics and Management 4,1(1991):33–50.

Bennett, J., Greene, G., Schwartz-Barcott, D., 2013. Perceptions of emotional eating behavior. A qualitative study of college students. Appetite, 60(1), 187-192.

Bin, Yu, 2021. 最新一到五线城市排名官宣：“上北深广”再现，宁波重归新一线!

（附完整名单）www.yicai.com

Bonacich, P., 1987. Power and centrality: A family of measures. American Journal of Sociology, 92, 1170-1182.

Borgatti, S.P., Everett, M.G., 2000. Models of corerperiphery structures Stephen. Social Networks, 21, 375–395.

Borgatti, S.P., Everett, M.G., Freeman, L.C., 2002. UCInet for Windows: Software for Social Network Analysis. (Harvard: Analytic Technologies)

Bradley, M., and A. Daly, 1994. Use of the logit scaling approach to test for rank-order and fatigue effects in stated preference data. Transportation 21(2):167–184.

Brehm, J.M., B.W. Eisenhauer, Krannich, R.S. 2004. Dimensions of community attachment and their relationship to well-being in the amenity-rich rural west. Rural Sociology 69(3):405–429.

Brick, K. and Visser, M., 2015. Risk preferences, technology adoption and insurance uptake: A framed experiment. Journal of Economics and Behavioral Organization, 118, 383–396.

Caputo, V. 2020. Does information on food safety affect consumers' acceptance of new food technologies? The case of irradiated beef in South Korea under a new labelling system and across different information regimes. Australian Journal of Agricultural and Resource Economics 64(4):1003–1033.

Caputo, V., R. Scarpa, and R.M. Nayga. 2017. Cue versus independent food attributes: The effect of adding attributes in choice experiments. European Review of Agricultural Economics 44(2):211–230.

Caputo, V., R.M. Nayga, and R. Scarpa, 2013. Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study. Australian Journal of Agricultural and Resource Economics 57(4):465–482.

Carlsson, F., M. Morten Raun, and S.B. Olsen. 2012. The first time is the hardest: A test of ordering effects in choice experiments. Journal of Choice Modelling 5(2):19–37.

Caswell, J.A., and E.M. Mojduszka, 1996. Using Informational Labeling to Influence the Market for Quality in Food Products. American Journal of Agricultural Economics 78(5):1248–1253.

Chen, J., M. Liu., and L. Zong, 2012. The fractal dimension research of Chinese and American beef marbling standards images. In International Conference on Computer and Computing Technologies in Agriculture (pp. 199-209). Springer, Berlin, Heidelberg.

[dataset]China Customs statistics, 2022. http://43.248.49.97.

China Green Food Development Center, 2011. Logo implication. http://www.greenfood.agri.cn/ywlssp/agf/Polices/201108/t20110803_2102224.htm

Choicemetrics, 2021. Ngene 1.3 User manual and reference guide. http://www.choice-metrics.com/NgeneManual130.pdf.

Chow, E. K., 2019. China's gmo paradox. Retrieved from https://thediplomat.com/2019/05/chinas-gmo-paradox/

Chung, C., B.C. Briggeman, and S. Han. 2012. Willingness-to-Pay for Beef Quality Attributes: A Latent Segmentation Analysis of Korean Grocery Shoppers. Journal of Agricultural and Applied Economics 44(4):447–459.

Chung, C., T. Boyer, and S. Han, 2009. Valuing quality attributes and country of origin in the Korean beef market. Journal of Agricultural Economics 60(3):682–698.

Conley, T., C.R. Udry, 2001. Social Learning through Networks : The Adoption of New Agricultural Technologies in Ghana. American Journal of Agricultural Economics, 83, 668–673.

Conley, T.G., C.R. Udry, 2010. Learning about a new technology: pineapple in Ghana. American Economic Review, 100:35–69.

Cronbach, L.J., 1951. Coefficient alpha and the internal structure of tests. Psychometrika, 16, 297–334.

Cummings, R.G., and L.O. Taylor. 1999. Unbiased value estimates for environmental goods: A cheap talk design for the contingent valuation method. American Economic Review 89(3):649–665.

Cunningham, Edward, Tony Saich, and Jessie Turiel. 2020. Understanding CCP Resilience: Surveying Chinese Public Opinion Through Time. Ash Center for Democratic Governance and Innovation.

Dagger, T.S., and M.M. Raciti. 2011. Matching consumers ' country and product image perceptions : an Australian perspective. Journal of Consumer Marketing 28:200–210.

Daly, A., S. Hess, and G. de Jong, 2012. Calculating Errors for Measures Derived from Choice Modelling Estimates. Transportation Research Part B: Methodological 46 (2): 333–41.

Day, C., 2015. PRRS-resistant pigs: a genetic showstopper. Retrieved from https://www.nationalhogfarmer.com/animal-well-being/prrs-resistant-pigs-genetic-showstopper

Deloitte, 2010. Winning the wallet of today's Chinese consumers - A look at consumer buying preferences. https://www2.deloitte.com/cn/en/pages/finance/articles/winning-the-wallet-of-today-chinese-consumers.html.

Delong, K.L., and C.O. Trejo-pech. 2022. Factors Affecting Sugar-Containing-Product Prices. Journal of Agricultural and Applied Economics 54:334–356.

Deng, H., Hu, R., Huang, J., Pray, C., Jin, Y., Li, Z., 2017. Attitudes toward GM foods, biotechnology R&D investment and lobbying activities among agribusiness firms in the food, feed, chemical and seed industries in China. China Agricultural Economic Review, 9, 385–396.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., 2010. Are risk aversion and impatience related to cognitive ability? American Economic Review, 100, 1238–1260.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economics Association, 9, 522–550.

Dworkin, S.L., 2012. Sample Size Policy for Qualitative Studies Using In-Depth Interviews. Archives of Sexual Behavior, 41, 1319–1320.

Ehmke, M.D., J.L. Lusk, and W. Tyner. 2008. Measuring the relative importance of preferences for country of origin in China, France, Niger, and the United States. Agricultural Economics 38:277–285.

Fang, S., X. Li, and A.Y. Liu. 2022. Chinese Public Opinion about US–China Relations from Trump to Biden. The Chinese Journal of International Politics 15(1):27–46.

Fei, X. (Hsiao-Tung), 1947. Xiangtu Zhongguo (From the Soil). Shanghai: Guanchashe.

Feld, S.L. 1991. Why Your Friends Have More Friends than You Do. American Journal of Sociology, 96(6),1464–1477.

Foster, A.D., Rosenzweig, M.R., 1995. Learning by Doing and Learning from Others : Human Capital and Technical Change in Agriculture. Journal of Political Economy, 103, 1176–1209.

Freeman, L. C. 1973. Centrality in social networks: Conceptual clarification. Social Networks, 1(3), 215-239.

Freeman, L.C., 1979. Centrality in social networks: Conceptual clarification. Social Networks, 1(3), 215-239.

Freudenreich, H., Mußhoff, O., 2018. Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico. Journal of Agricultural Economics, 69, 96–120.

Gale, F. and K. Huang, 2007. Demand for Food Quantity and Quality in China. USDA Department of Agriculture Economic Research Report 31.

Galindo, I., Alonso, C., 2017. African swine fever virus: A review. Viruses, 9(5).

Gao, S., C. Grebitus, and T.G. Schmitz. 2022. "Effects of Risk Preferences and Peer Influence on Adoption of Genomics by Chinese Hog Farmers." Journal of Rural Studies 94:111–127

Gao, Y., Zhao, D., Yu, L., Yang, H., 2020. Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. Journal of Rural Studies, 76, 173–183.

Gava, O., E. Favilli, F. Bartolini, and G. Brunori. 2017. Knowledge networks and their role in shaping the relations within the Agricultural Knowledge and Innovation System in the agroenergy sector. The case of biogas in Tuscany (Italy). Journal of Rural Studies 56:100–113.

Gerrits, R.J., Lunney, J.K., Johnson, L.A., Pursel, V.G., Kraeling, R.R., Rohrer, G.A., Dobrinsky, J.R., 2005. Perspectives for artificial insemination and genomics to improve global swine populations. Theriogenology, 63, 283–299.

Ghorbani, M., S.A. Javadi, S. Rasekhi, M. Yazdanparast, Azadi, H. 2022. Bonding Social Capital of Rural Women in Southwest Iran: Application of Social Network Analysis. Rural Sociology 0(0):1–26.

Gillespie, J.M., Davis, C.G., Rahelizatovo, N.C., 2004. Factors Influencing the Adoption of Breeding Technologies in U.S. Hog Production. Journal of Agricultural and Applied Economics, 36(1), 35–47

Godfarb, Daniele, Mercedes Fogarassy, Shaelyn Laurie. 2021. Chinese perceptions of the US. Retrieved from https://riwi.com/research/chinese-perceptions-of-the-us/.

Gong, L., Xu, R., Wang, Z., Deng, Q., Wang, H., Zhang, G., 2020. African swine fever recovery in China. Veterinary Medical Science, 1–4.

Granovetter, M.S., 1973. The Strength of Weak Ties. American Journal of Sociology, 78(6), 1360-1380.

Grebitus, C., 2008. Food quality from the consumer's perspective: an empirical analysis of perceived pork quality. Goettingen, Germany: Cuvillier Verlag.

Grebitus, C., and E.J. Van Loo. 2022. Relationship between cognitive and affective processes, and willingness to pay for pesticide-free and GMO-free labeling. Agricultural Economics 53(3):407–421.

Grebitus, C., J.L. Lusk, and R.M. Nayga. 2013. Effect of distance of transportation on willingness to pay for food. Ecological Economics 88:67–75.

Greene, William H., 2012. Econometric Analysis (Seventh ed.). Boston: Pearson Education.

Gyau, A., Voss, J., Spiller, A., Enneking, U., 2009. Farmer acceptance of genetically modified seeds in Germany: Results of a cluster analysis. International Food and Agribusiness Management Review, 12, 61–80.

Hailu, G., Cao, Y., Yu, X., 2017. Risk Attitudes, Social Interactions, and the Willingness to Pay for Genotyping in Dairy Production. Canadian Journal of Agricultural Economics, 65, 317–341.

Han, C.M. 1989. Country Image: Halo or Summary Construct? Journal of Marketing XXVI:222–229.

Han, C.M., and C. Guo. 2018. How Consumer Ethnocentrism (CET), Ethnocentric Marketing , and Consumer Individualism Affect Ethnocentric Behavior in China. Jounral of Global Marketing 31(5):324–338.

Hanneman, R.A., Riddle, M., 2005. Introduction to social network methods. (University of California, Riverside).

He, J., and C.L. Wang. 2015. Cultural identity and consumer ethnocentrism impacts on preference and purchase of domestic versus import brands: An empirical study in China. Journal of Business Research 68:1225–1233.

Hensher, D. A., J. M. Rose, and W. H. Greene. 2005. Applied Choice Analysis: A Primer. Cambridge: Cambridge University Press.

Herche, Joel. 1992. A Note on the Predictive Validity of the CETSCALE. Journal of the Academy of Marketing Science, 20 (3), 261–64.

Hess, S., Hensher, D. and Daly, A.J., 2012. Not bored yet - revisiting respondent fatigue in stated choice experiments. Transportation Research Part A: Policy and Practice, 46 (3). 626 – 644.

Holloway, G., Shankar, B., Rahman, S., 2002. Bayesian spatial probit estimation: A primer and an application to HYV rice adoption. Agricutral Economics, 27, 383–402.

Holt, C.A., Laury, S.K., 2002. Risk aversion and incentive effects. Am. Econ. Rev. 95, 1644–1655.

Hu, D. 2021. Public Sentiment in China Cools towards Australia. Retrieved from https://pursuit.unimelb.edu.au/articles/public-sentiment-in-china-cools-towards-australia.

Huang, J., Hu, R., Rozelle, S., Pray, C., 2005. Plant science: Insect-resistant GM rice in farmers' fields: Assessing productivity and health effects in China. Science (80-.). 308, 688–690.

Huang, J.K., Peng, B., 2015. Consumers' perceptions on GM food safety in urban China. Journal of Integrative Agriculture, 14(11), 2391-2400.

Hunold, C., Sorunmu, Y., Lindy, R., Spatari, S., Gurian, P. 2017. Is urban agriculture financially sustainable? An exploratory study of small-scale market farming in Philadelphia, Pennsylvania. Journal of Agriculture, Food Systems, and Community Development, 7(2), 51-67.

Iles, K., Z. Ma, and A. Erwin. 2020. Identifying the common ground: Small-scale farmer identity and community revised and resubmitted to the journal of rural studies. Journal of Rural Studies 78:25–35.

Jäckering, L., T. Gödecke, and M. Wollni. 2019. Agriculture–nutrition linkages in farmers' communication networks. Agricultural Economics 50(5):657–672.

Jackson, M.O., 2008. Social and Economic Networks. (Princeton NJ: Princeton University Press).

Jensen, R. 2007. The digital divide: information (technology), market performance, and welfare in the south Indian fisheries sector. The quarterly journal of economics 122(3):879–924.

Jianjun, J., Yiwei, G., Xiaomin, W., Nam, P.K., 2015. Farmers' risk preferences and their climate change adaptation strategies in the Yongqiao District, China. Land Use Policy, 47, 365–372.

Johny, J., B. Wichmann, and B.M. Swallow. 2017. Characterizing social networks and their effects on income diversification in rural Kerala, India. World Development 94:375–392.

Josiassen, A. 2011. Consumer Disidentification and Its Effects on Domestic Product Purchases: An Empirical Investigation in the Netherlands. Journal of Marketing 75(2):124–140.

Kaiser, H.F.1958. The varimax criterion for analytic rotation in factor analysis. Psychometrika 23, 187–200.

Kaiser, H.F., 1970. A second generation little jiffy. Psychometrika 35, 401–415.

Kaiser, H.F, 1974. An index of factorial simplicity. Psychometrika 39, 31–36.

Kilders, V., V. Caputo, and L.S.O. Liverpool-tasie. 2021. Consumer ethnocentric behavior and food choices in developing countries : The case of Nigeria. Food Policy 99:101973.

Klein, J.G., R. Ettenson, and M.D. Morris. 1998. The Animosity Model of Foreign Product Purchase: An Empirical Test in the People's Republic of China. Journal of Marketing 62(1):89–100.

Knoke, D., Kuklinski, J., 1982. Network analysis. Series: Quantitative applications in the social sciences /number 07-028. (SAGE Publications, Newbury Park, UK).

Kolbasov, D., Titov, I., Tsybanov, S., Gogin, A., Malogolovkin, A., 2018. African swine fever virus, Siberia, Russia, 2017. Emerging Infectious Diseases, 24(4), 796–798.

Krinsky, I., and Robb, A.L., 1986. On approximating the statistical properties of elasticities. The Review of Economics and Statistics. 64 (4), 715–719.

Krishnan, P., Patnam, M., 2014. Neighbors and extension agents in ethiopia: Who matters more for technology adoption? American Journal of Agricultural Economics, 96, 308–327.

Kumar, A., Epley, N. 2020. It's Surprisingly Nice to Hear You: Misunderstanding the Impact of Communication Media Can Lead to Suboptimal Choices of How to Connect With Others. Journal of Experimental Psychology: General 2(999).

Lachal, J., Speranza, M., Taïeb, O., Falissard, B., Lefèvre, H., Moro, M.R.., Revah-Levy, A.Q., 2012. Qualitative research using photo-elicitation to explore the role of food in family relationships among obese adolescents. Appetite, 58(3), 1099-1105.

Lancaster, K.J. 1966. A New Approach to Consumer Theory. Journal of Political Economy 74(2):132–157.

Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K., M., Menczer, F., …Zittrain, J. L. 2018. The science of fake news. Science, 9, 1094–1096.

Lee, D.R., 2005. Agricultural sustainability and technology adoption:issues And policies for developing countries. American Journal of Agricultural Economics, 87, 1325–1334.

Leung, N., J. Ngai, J. Seong, and J. Woetzel, 2020. Fast forward China: How COVID-19 is accelerating 5 key trends shaping the Chinese economy. McKinsey & Company.

Lewis, K.E., and C. Grebitus. 2016. "Why U.S. Consumers Support Country of Origin Labeling: Examining the Impact of Ethnocentrism and Food Safety." Journal of International Food and Agribusiness Marketing 28(3):254–270.

Lewis, K.E., C. Grebitus, G. Colson, and W. Hu. 2017. German and British Consumer Willingness to Pay for Beef Labeled with Food Safety Attributes. Journal of Agricultural Economics 68(2):451–470.

Liang, R. R., H. Zhu, Y. W. Mao, Y. M. Zhang, L. X. Zhu, D. Cornforth, R. H. Wang, X. Y. Meng, and X. Luo, 2016. Tenderness and sensory attributes of the longissimus lumborum muscles with different quality grades from Chinese fattened yellow crossbred steers. Meat science 112: 52-57.

Lin, W., D.L. Ortega, D. Ufer, V. Caputo, and T. Awokuse. 2020. Blockchain-based traceability and demand for U.S. beef in China. Applied Economic Perspectives and Policy (August):1–20.

Lippit, N. P., R., Rosen, S., 1952. The dynamics of power a case study of social influence in groups of children. Human Relations, 5, 37-64.

Liu, E.M., 2013. Time to change what to sow : risk preferences and technology adoption decisions of cotton farmers in china. Review of Economics and Statistics, 95, 1386–1403.

Liu, Z. 2019. Chinese criminal gangs spreading African swine fever to force farmers to sell pigs cheaply so they can profit. Retrieved from https://www.scmp.com/news/china/politics/article/3042122/chinese-criminal-gangs-spreading-african-swine-fever-force.

Lusk, J.L. 2003. Effects of Cheap Talk on Consumer Willingness-to-Pay for Golden Rice Published. American Journal of Agricultural Economics 85(4):840–856.

Lusk, J.L., and G.T. Tonsor. 2016. How Meat Demand Elasticities Vary with Price , Income , and Product Category. Applied Economic Perspectives and Policy 38(4):673–711.

Lusk, J.L., and T.C. Schroeder. 2004. Are Choice Experiments Incentive Compatible ? A Test with Quality Differentiated Beef Steaks. American Journal of Agricultural Economics 86(2):467–482.

Lusk, J.L., G.T. Tonsor, T.C. Schroeder, and D.J. Hayes, 2018. Effect of government quality grade labels on consumer demand for pork chops in the short and long run. Food Policy 77:91–102.

Lusk, J.L., J. Brown, T. Mark, I. Proseku, R. Thompson, and J. Welsh. 2006. Consumer Behavior, Public Policy, and Country-of-Origin Labeling. Review of Agricultural Economics 28(2):284–292.

Marsden, P. V., Friedkin, N. E., 2013. Network studies of social influence. Sociological Methods and Research, 22, 127–151.

Marsden, P.V., Campbell, K.E. 1984. Measuring tie strength. Social Forces 63(2): 482–501.

Martin, I.M. and Eroglu, S. (1993). Measuring a multidimensional construct: country image. journal of Business Research 28(3): 191-210.

Matuschke, I., Qaim, M., 2009. The impact of social networks on hybrid seed adoption in India. Agricultural Economics, 40, 493–505.

Mazur-Panasiuk, G.N.K., Wozniakowski, N. 2019. The first complete genomic sequences of african swine fever virus isolated in Poland. Scientific Reports, 9(4556).

McFadden, D. 1974. Conditional logit analysis of qualitative choice behavior (pp. 105–142). New York: Academic Press.

Menapace, L., Colson, G., Raffaelli, R., 2016. A comparison of hypothetical risk attitude elicitation instruments for explaining farmer crop insurance purchases. European Review of Agricultural Economics, 43, 113–135.

Merritt, M.G., K.L. DeLong, A.P. Griffith, and K.L. Jensen. 2018. Consumer willingness to pay for Tennessee certified beef. Journal of Agricultural and Applied Economics 50(2):233–254.

Mills, J., M. Reed, K. Skaalsveen, Ingram, J. 2019. The use of Twitter for knowledge exchange on sustainable soil management. Soil Use and Management 35(1):195–203.

Mitter, H., Larcher, M., Schönhart, M., Stöttinger, M., Schmid, E. 2019. Exploring Farmers' Climate Change Perceptions and Adaptation Intentions. Empirical Evidence from Austria. Environmental Management, 63, 804–821.

Nagashima, A. 1970. A comparison of japanese and US attitudes toward foreign products. Journal of Marketing 34(1): 68-74.

Nagashima, A. 1977. A comparative "made in" product image survey among japanese businessmen. Journal of Marketing 41(2): 95-100.

National public service platform for standards information (NPSP), 2021a. Quality grading of livestock and poultry meat-beef. http://std.samr.gov.cn/gb/search/gb Detailed?id=9BFD0CB5242A2840E05397BE0A0A4BE5.

Nie, W., D. Abler, and T. Li, 2021. Grading attribute selection of China's grading system for agricultural products: What attributes benefit consumers more? Journal of Behavioral and Experimental Economics 93:101707.

Nie, W., T. Li, and L. Zhu, 2020. Market demand and government regulation for quality grading system of agricultural products in China. Journal of Retailing and Consumer Services 56(December 2018):102134.

Nie, X., J. Zhou, P. Cheng, and H. Wang. 2021. Exploring the differences between coastal farmers' subjective and objective risk preferences in China using an agent-based model. Journal of Rural Studies 82:417–429.

Ning, Pan 2020. 全球 33 国对美中态度如何？日本人最反感中国. Retrieved from https://www.abc.net.au/chinese/2020-01-17/pew-survey-on-global-attitudes-on-us-and-china/11878098.

NPSP, 2021b. 国家标准《畜禽肉质量分级 牛肉》（征求意见稿）编制说明. http://file2.foodmate.net/wenku2021/wlx202101210846.pdf

NPSP, 2021c. 畜禽肉质量分级 牛肉. http://file2.foodmate.net/wenku2021/wlx202101210845.pdf

Oberecker, E.M., P. Riefler, and A. Diamantopoulos. 2008. The Consumer Affinity Construct : Conceptualization , Qualitative Investigation , and Research Agenda Adamantios Diamantopoulos. Jounral of International Marketing 16(3):23–56.

OECD, 2021. Meat consumption. https://data.oecd.org/agroutput/meat-consumption.htm

Ortega, D.L., H.H. Wang, L. Wu, and N.J. Olynk, 2011. Modeling heterogeneity in consumer preferences for select food safety attributes in China. Food Policy 36(2):318–324.

Ortega, D.L., J. Sun, and W. Lin. 2022. Identity labels as an instrument to reduce meat demand and encourage consumption of plant based and cultured meat alternatives in China. Food Policy 111:102307.

Ortega, D.L., M. Chen, H.H. Wang, and S. Shimokawa, 2017. Emerging Markets for U. S. Pork in China: Experimental Evidence from Mainland and Hong Kong Consumers. Journal of Agricultural and Resource Economics 42(2):275–290.

Ortega, D.L., S.J. Hong, H.H. Wang, and L. Wu, 2016. Emerging markets for imported beef in China: Results from a consumer choice experiment in Beijing. Meat Science 121:317–323.

Ortega, D.L., W. Lin, and P.S. Ward. 2022. Consumer acceptance of gene-edited food products in China. Food Quality and Preference 95.

Palma, M.A., M.D. Johnson, and D.P. Anderson, 2018. The effects of experience versus description of attributes on willingness-to-pay for beefsteaks. Agricultural Economics 0:1–9.

Pappu, R., P.G. Quester, and R.W. Cooksey. 2007. Country image and consumer-based brand equity : relationships and implications for international marketing. :726–745.

Peschel, A.O., C. Grebitus, G. Colson, and W. Hu. 2016. Explaining the use of attribute cut-off values in decision making by means of involvement. Journal of Behavioral and Experimental Economics 65:58–66.

Peterson, H.H., and L.D. Burbidge. 2012. Japanese consumers' valuation of U.S. beef and pork products after the Beef Trade Ban. Journal of Agricultural and Resource Economics 37(1):58–76.

Printezis, I., and C. Grebitus, 2018. Marketing Channels for Local Food. Ecological Economics 152:161–171.

Qing, P., A. Lobo, and L. Chongguang. 2012. The impact of lifestyle and ethnocentrism on consumers' purchase intentions of fresh fruit in China. Journal of Consumer Marketing 29(1):43–51.

Qiu, Y., Colson, G., Grebitus, C., 2014. Risk preferences and purchase of energy-efficient technologies in the residential sector. Ecological Economics, 107, 216–229.

Quembo, C. J., Jori, F., Vosloo, W., Heath, L. 2018. Genetic characterization of African swine fever virus isolates from soft ticks at the wildlife/domestic interface in Mozambique and identification of a novel genotype. Transboundary and emerging diseases, 65 (2), 420–431.

Ramirez, A. 2013. The Influence of Social Networks on Agricultural Technology Adoption.

Procedia - Social and Behavioral Sciences 79:101–116.

Ramsey, S.M., Bergtold, J.S., Canales, E., Williams, J.R., 2019. Effects of farmers' yield-risk perceptions on conservation practice adoption in Kansas. Journal of Agricultural Resource Economics, 44, 380–403.

Reuters, 2020. China floods blamed for fresh African swine fever outbreaks Retrieved from https://www.reuters.com/article/us-china-swinefever-floods/china-floods-blamed-for-fresh-african-swine-fever-outbreaks-idUSKBN24B0ZF

Reuters, 2020. China further eases US beef and beef product import curbs. https://www.reuters.com/article/us-usa-trade-china-beef/china-further-eases-u-s-beef-and-beef-product-import-curbs-idUSKCN20I0SN.

Reuters. 2020. China to probe labs, farms in crackdown on illegal African swine fever vaccines. Retrieved from https://www.reuters.com/article/us-china-swinefever-vaccine/china-to-probe-labs-farms-in-crackdown-on-illegal-african-swine-fever-vaccines-idUSKBN25L142

Rogers, E.M., 2003. Diffusion of Innovations. Free Press, New York

Roghanizad, M.M., Bohns, V.K. 2017. Ask in person: You're less persuasive than you think over email. Journal of Experimental Social Psychology 69: 223–226.

Rosburg, A., Menapace, L., 2018. Factors influencing corn fungicide treatment decisions. Journal of Agricultural Resource Economics, 43, 151–171.

Rothschild, M.; Stalder, K., Dekkers, J., 2010. Genomic Selection Shows Promise in Swine Breeding. https://www.nationalhogfarmer.com/genetics-reproduction/evaluation-selection/genomic-selection-tools-0426

Sadikaj, G., Moskowitz, D.S., 2018. I hear but I don't see you: Interacting over phone reduces the accuracy of perceiving affiliation in the other. Computers in Human Behavior, 89(April), 140–147.

Santos, J.A. dos, L.B. Roldan, and M.K.L. Loo. 2021. Clarifying relationships between networking, absorptive capacity and financial performance among South Brazilian farmers. Journal of Rural Studies 84:90–99.

Savage, S.J., and D.M. Waldman, 2008. Learning and fatigue during choice experiments: A comparison of online and mail survey modes. Journal of Applied Econometrics 23:351–371.

Scarpa, R., and J.M. Rose, 2008. Design efficiency for non-market valuation with choice modelling: How to measure it, what to report and why. Australian Journal of

Agricultural and Resource Economics 52(3):253–282.

Scarpa, R., D. Campbell, and W.G. Hutchinson, 2007a. Benefit Estimates for Landscape Improvements: Sequential Bayesian Design and Respondents' Rationality in a Choice Experiment Study. Land Economics 83,4:617–34.

Scarpa, R., Ferrini, S. and Willis, K.G., 2005a. Performance of Error Component Models for Status Quo Effects in Choice Experiment, in: Scarpa, R. and Alberini, A. (eds), Applications of Simulation Method in Environmental and Resource Economics. Springer, Dordrecht, Netherlands, pp. 247–274.

Scarpa, R., K.G. Willis, and M. Acutt, 2007b. Valuing externalities from water supply: Status quo, choice complexity and individual random effects in panel kernel logit analysis of choice experiments. Journal of Environmental Planning and Management 50(4):449–466.

Scarpa, R., K.G. Willis, and M. Acutt. 2007. Valuing externalities from water supply: Status quo, choice complexity and individual random effects in panel kernel logit analysis of choice experiments. Journal of Environmental Planning and Management 50(4):449–466.

Scarpa, R., R. Zanoli, V. Bruschi, and S. Naspetti, 2013. Inferred and Stated Attribute Nonattendance in Food Choice Experiments." American Journal of Agricultural Economics 95,1:165–80.

Scarpa, R., Willis, K.G. and Acutt, M., 2005b. Individual-specific welfare measures for public goods: a latent class approach to residential customers of Yorkshire Water, in: Koundouri, P. (ed), Econometrics Informing Natural Resource Management, Edward Elgar Publisher, Northampton, MA, USA. pp. 316–337.

Seitz, C.C., and J. Roosen. 2015. Does consumer ethnocentrism influence product knowledge ? Food Quality and Preference 43:113–121.

Shankarmahesh, M.N. 2006. Consumer ethnocentrism: An integrative review of its antecedents and consequences. International Marketing Review 23(2):146–172.

Shao, Y., Li, M., Zhang, W., Ji, Y., Hayes, D.J., 2018. World's Largest Pork Producer in Crisis: China's African Swine Fever Outbreak. CARD Agricultural Policy Review, 3, https://lib.dr.iastate.edu/agpolicyreview/vol2018/iss3/1/

Shimp, T.A., and S. Sharma. 1987. Consumer Ethnocentrism: Construction and Validation of the CETSCALE. Journal of Marketing Research 24(3):280.

Shuping, N. 2019. Chinese hog farms "Panic" as swine virus continues roiling herds". Sociology, 78(May), 1360-80.

Silver, Laura, Fagan, M., Connaughton, A. and Mordecai, M. 2021. About Pew Research Center's Fall 2020 Global Attitudes Survey. Retrieved from https://www.pewresearch.org/global/2021/05/05/cultural-grievances-methodology/.

Silver, Laura. 2021. China's international image remains broadly negative as views of the U.S. rebound. Retrieved from https://www.pewresearch.org/fact-tank/2021/06/30/chinas-international-image-remains-broadly-negative-as-views-of-the-u-s-rebound/

Sina, 2019. 全国吃肉图鉴丨猪鸡牛羊肉消费大省分别是哪些?. Retrieved from https://cj.sina.com.cn/articles/view/7239693013/1af84f2d500100lb0q

Skaalsveen, K., J. Ingram, Urquhart, J. 2020. The role of farmers' social networks in the implementation of no-till farming practices. Agricultural Systems. 181(102824).

Sonneville, K.R., La Pelle, N., Taveras, E.M. et al., 2009. Economic and other barriers to adopting recommendations to prevent childhood obesity: results of a focus group study with parents. BMC Pediatrics, 9, 81.

Street, D. J., and Burgess, L., 2007. The construction of optimal stated choice experiments. Hoboken: John Wiley & Sons.

Syrengelas, K.G., K.L. DeLong, C. Grebitus, and R.M. Nayga. 2018. Is the Natural Label Misleading? Examining Consumer Preferences for Natural Beef. Applied Economic Perspectives and Policy 40(3):445–460.

Takahashi, B., Burnham, M., Terracina-Hartman, C., Sopchak, A.R., Selfa, T., 2016. Climate Change Perceptions of NY State Farmers: The Role of Risk Perceptions and Adaptive Capacity. Environmental Management, 58, 946–957.

Texas A&M. 2022. Meat Science: USDA Beef Quality and Yield Grades. https://meat.tamu.edu/beefgrading/

The Economist. 2022. China says imports are causing outbreaks of covid-19. Retrieved from https://www.economist.com/china/2022/04/21/china-says-imports-are-causing-outbreaks-of-covid-19

Thompson, J. 2021. Watching Together: Local Media and Rural Civic Engagement. Rural Sociology 86(4):938–967.

Tonsor, G.T., and R.S. Shupp. 2011. Cheap talk scripts and online choice experiments: 'Looking beyond the mean.' American Journal of Agricultural Economics 93(4):1015–1031.

Train, K., 2009. Discrete Choice Methods with Simulation. Cambridge: Cambridge University Press

Train, K., and M. Weeks. 2005. Discrete Choice Models in Preference Apace and Willingness-to-Pay Space. In Applications of Simulation Methods in Environmental Resource Economics. pp. 1–17.

USDA Agricultural Marketing Service. 2022. Public Grading Dashboard. https://public.tableau.com/app/profile/agricultural.marketing.service.livestock.and.poultry.program/viz/LPPublicGradingDashboard/AMSLPLandingPage

USDA, 2019. China Publishes New Organic Standard and Certification Rules. https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=China%20Publishes%20New%20Organic%20Standard%20and%20Certification%20Rules_Beijing_China%20-%20Peoples%20Republic%20of_12-02-2019

USDA, 2019. Disease Response Strategy: African Swine Fever. URL https://www.aphis.usda.gov/animal_health/emergency_management/downloads/asf_strategies.pdf

USDA, 2019. Livestock and poultry: world markets and trade, United States Department of Agriculture and Foreign Agricultural Service. https://doi.org/10.1016/S1097-8690(11)70006-3

USDA, 2019. Livestock and poultry: world markets and trade. https://downloads.usda.library.cornell.edu/usda-esmis/files/73666448x/g445ct12h/ff365k146/Livestock_poultry.pdf

USDA, 2020. Planning and Preparing for African Swine Fever-Quick Briefing. URL https://www.aphis.usda.gov/animal_health/emergency_management/downloads/asf-briefing-plan-prepare.pdf

USDA, 2022. Livestock and poultry: world markets and trade. https://apps.fas.usda.gov/psdonline/circulars/livestock_poultry.pdf.

Vainio, A., R. Paloniemi, and T. Hujala. 2018. How are forest owners' objectives and social networks related to successful conservation? Journal of Rural Studies 62:21–28.

Van Gilder, B., Abdi, S., 2014. Identity management and the fostering of network ignorance: Accounts of queer Iranian women in the United States. Journal of Intercultural Communication Research, 43(2), 151-170.

Van Loo, E.J., C. Grebitus, and J. Roosen. 2019. Explaining attention and choice for origin labeled cheese by means of consumer ethnocentrism. Food Quality and Preference 78(May):103716.

Van Loo, E.J., V. Caputo, and J.L. Lusk. 2020. Consumer preferences for farm-raised meat, lab-grown meat, and plant-based meat alternatives: Does information or brand matter? Food Policy 95(August 2019):101931.

Van Wezemael, L., V. Caputo, R.M. Nayga, G. Chryssochoidis, and W. Verbeke. 2014. European consumer preferences for beef with nutrition and health claims: A multi-country investigation using discrete choice experiments. Food Policy 44:167–176.

Verlegh, P.W.J., and J.B.E.M. Steenkamp. 1999. A review and meta-analysis of country-of-origin research. Journal of Economic Psychology 20:521–546.

Vosoughi, S., Roy, D., Aral, S. 2018. The spread of true and false news online. Science, 359, 1146–1151.

Wang, C.L., D. Li, B.R. Barnes, and J. Ahn. 2012. “Country image, product image and consumer purchase intention: Evidence from an emerging economy.” International Business Review 21:1041–1051.

Wang, Q., 2015. China’s scientists must engage the public on GM: the country’s shifting stance on genetic modification for crops needs the support of researchers to persuade a sceptical public. Nature, 519, 7–8.

Wang, Y., Q. Zhang, Q. Li, J. Wang, S. Sannigrahi, R. Bilsborrow, S.D. Bellingrath-Kimura, J. Li, and C. Song. 2021. Role of social networks in building household livelihood resilience under payments for ecosystem services programs in a poor rural community in China. Journal of Rural Studies 86:208–225.

Ward, P.S., Pede, V.O., 2015. Capturing social network effects in technology adoption: The spatial diffusion of hybrid rice in Bangladesh. Australian Journal of Agricultural Resource Economics, 59, 225–241.

Wasserman, S., Faust, K., 1999. Social Network Analysis. Methods and Applications. Structural analysis in the social sciences. (Cambridge University Press, Cambridge, USA, 8th edition).

Whitworth, K.M., Rowland, R.R.R., Ewen, C.L., Trible, B.R., Kerrigan, M.A., Cino-Ozuna, A.G., Samuel, M.S., Lightner, J.E., McLaren, D.G., Mileham, A.J., Wells, K.D., Prather, R.S., 2016. Gene-edited pigs are protected from porcine reproductive and respiratory syndrome virus. Nature Biotechnology, 34, 20–22.

Xia, H., C. Li, D. Zhou, Y. Zhang, and J. Xu. 2020. Peasant households’ land use decision-making analysis using social network analysis: A case of Tantou Village, China. Journal of Rural Studies 80:452–468.

Xia, L., 2019. Outbreaks of African Swine Fever contained. Retrieved from http://www.xinhuanet.com/english/2019-04/23/c 138002298.htm

Xin, L., and S.S. Seo. 2020. "The role of consumer ethnocentrism, country image, and subjective knowledge in predicting intention to purchase imported functional foods." British Food Journal 122(2):448–464.

Xin, X. 2019. China Focus: Pig farmers keen on expanding stock as China drums up pork production", Retrieved from http://www.xinhuanet.com/english/2019-11/23/c_138578469.htm

Xinhua News, 2019. Majority of Chinese consumers more focused on quality: survey. http://www.xinhuanet.com/english/2019-12/08/c_138615117.htm

Xu, R., Wu, Y., Luan, J., 2016. Analysis of farmers' willingness to adopt genetically modified insect-resistant rice in China. China Agricultural Economics Review, 8, 368–382.

Yang, R., K.C. Raper, and J.L. Lusk. 2020. Impact of hormone use perceptions on consumer meat preferences. Journal of Agricultural and Resource Economics 45(1):107–123.

Yeh, C., C. Chen, and P.J. Sher. 2010. "Investigation on perceived country image of imported food." Food Quality and Preference 21:849–856.

Yin, S., F. Han, Y. Wang, W. Hu, and S. Lv. 2019. Ethnocentrism, trust, and the willingness to pay of Chinese consumers for organic labels from different countries and certifiers. Journal of Food Quality 2019(Article ID 8173808, 13 pages).

Yu, X., Z. Gao, and Y. Zeng, 2014. Willingness to pay for the 'Green Food' in China. Food Policy 45:80–87.

Zhang, W., Hayes, D. J., Ji, Y., Li, M., Zlong, T., 2019. African Swine Fever in China: An Update. CARD Agriculture Policy Review, 1(2).

Zhang, Y., S. Jin, Y.Y. Zhang, and X. Yu. 2020. "How country of origin influences Chinese consumers' evaluation of imported milk?" China Agricultural Economic Review 13(1):150–172.

Zhao, G. Q., Wu, Q., 2015. Nonlinear dynamics of pork price in China. Journal of Integrative Agriculture, 14(6), pp. 1115–1121.

Zhao, S., Yue, C., 2020. Risk preferences of commodity crop producers and specialty crop producers: An application of prospect theory. Agricultural Economics, 51, 359–372.

Zheng, S., Wang, Z., Wachenheim, C.J., 2019. Technology adoption among farmers in Jilin Province, China: The case of aerial pesticide application. China Agricultural Economics Review, 11, 206–216.

Zhou, G.H. 1998. Developing a Beef Grading System for China. In Reciprocal Meat Conference Proceedings. pp. 92–94.

Zipser, D., and Poh, F., 2021. Understanding Chinese Consumers: Growth Engine of the World; China Consumer Report 2021. McKinsey & Company: Shanghai, China, 2021.

APPENDIX A

INFORMATION SHEET FOR PARTICIPANTS

PLEASE TAKE TIME TO CAREFULLY READ THE FOLLOWING INSTRUCTIONS BEFORE PROCEEDING

Imagine you are in your usual grocery store and considering the purchase of beef flank. In the following you will see 12 choice tasks. All features of the beef flank in each choice task are identical except that they vary with regard to country of origin, price, organic/green labeling, whether or not the cattle were corn-fed or grass-fed, and the quality grade of the beef.

The characteristics that you will see are based on real products. In each choice task, please indicate the decision you would make based on your own preferences. Specifically, you are asked which product you would choose to purchase, compared to other products that will be visible to you on the screen. Alternatively, you may choose not to purchase either product. Please carefully examine each option before you make a decision and tick the decision that you would make based on your own preferences.

IMPORTANT

o CHOOSE one of the options on each page. Or you may choose NOT TO PURCHASE either product.

o Assume that the options on each page are the only ones available.

o Do NOT compare options on different pages.

The Chinese Ministry of Agriculture and Rural Affairs is considering implementation of a quality grading system for beef. According to the Chinese Ministry of Agriculture and Rural Affairs, “its basic concept is based on carcass grading based on marble pattern, physiological maturity, flesh color and fat color, which is consistent with beef quality grading systems in the United States, Australia, Japan, South Korea and other countries."

As you take this survey, please assume the following definitions for the beef quality grades of "Premium" and "Regular", which will appear on the beef flank:

- "**Premium**" is to be considered of a higher quality grade than beef that is labeled as "Regular." "Premium" indicates the highest quality beef that is produced from young, well-fed beef cattle. It has slightly abundant marbling.
- "**Regular**" indicates the beef is high quality, but has less marbling than "Premium" beef, but has at least a small amount of marbling.

You might see a few options that may seem counter-intuitive (e.g., a lower price but a higher quality in your personal opinion). Be assured that this is not an error but part of the design of the survey. Simply choose the option that you prefer most, based on its characteristics.

The experience from previous similar surveys is that people often state a higher willingness to pay than what one is actually willing to pay for the good. For instance, a recent study asked people whether they would purchase a new food product similar to the one you are about to be asked about. This purchase was hypothetical (as it will be for you) in that no one actually had to pay money when they indicated a willingness to purchase. In the study, 80% of people said they would buy the new product, but when a grocery store actually stocked the product, only 43% of people actually bought the new product when they had to pay for it. This difference (43% vs. 80%) is what we refer to as hypothetical bias. Accordingly, it is important that you make each of your upcoming selections like you would if you were actually facing these exact choices in a store, i.e., noting that buying a product means that you would have less money available for other purchases.

APPENDIX B

SPECIFIC SURVEY QUESTIONS

1. How favorable is your opinion of the following countries?

	Very unfavorable (1)	2	3	4	Very favorable (5)
China					
U.S.					
Australia					
Brazil					

2. Please select how much you agree or disagree with each statement below (strongly disagree=1 to strongly agree=7).

	Strongly Disagree						Strongly Agree
	1	2	3	4	5	6	7
Only those products that are unavailable in China should be imported.							
Chinese products first, last and foremost.							
Purchasing foreign-made products is un-Chinese.							
It is not right to purchase foreign products, because it puts Chinese people out of jobs.							
Real Chinese people should always buy Chinese-made products.							
We should purchase products manufactured in China instead of letting other countries get rich off us.							
Chinese people should not buy foreign products, because this hurts Chinese business and causes unemployment.							
It may cost me in the long run but I prefer to support Chinese products.							
We should buy from foreign countries only those products that we cannot obtain within our own country.							
Chinese consumers who purchase products made in other countries are responsible for putting their fellow Chinese people out of work							

3. In your opinion, how safe is beef from the following countries?

	Not very safe (1)	2	3	4	Very safe (5)
Safety of Chinese Beef					
Safety of U.S. Beef					
Safety of Australian beef					
Safety of Brazilian beef					

APPENDIX C

RESULTS FROM RPL MODELS

	RPL
Price	-0.01***
	(0.00)
Brazil	2.20***
	(0.13)
U.S.	2.69***
	(0.12)
Australia	3.02***
	(0.12)
China	3.71***
	(0.14)
Standard deviations of parameter distributions	
Brazil	0.81***
	(0.10)
US	0.98***
	(0.09)
Australia	0.87***
	(0.08)
China	2.02***
	(0.10)
N	5,022
LL	-5,919.31
AIC	11,856.6

APPENDIX D

INDIVIDUAL WILLINGNESS TO PAY FOR DOMESTIC AND IMPORTED BEEF FLANK COMPARED TO NOT CHOOSING BEEF (THE “NONE OF THESE” OPTION)

In Yuan/kg	Mean	S.D.	Min	Max
China	377.33	176.73	60.64	700.17
U.S.	272.16	60.72	128.24	454.42
Australia	306.60	51.82	169.25	486.31
Brazil	222.32	40.62	117.88	392.23

APPENDIX E

SURVEY QUESTIONS CORRESPONDING TO ANALYSIS

Note: Participants received a version translated to Chinese.

1. Are you: male _____ female____
2. How old are you? ____ years
3. What is the highest level of education that you have obtained?

Elementary school or below _____

Middle school_____

High school_____

College degree_____

Undergraduate or above_____

4. Which of the following best describes your operation in 2019?

Farrow-to-finish_____

Farrow-to-wean_____

Feeder_____

Breeding stock_____

Company & Farmers_____

5. Including 2019, for how many years have you been raising hogs? ______ years
6. What was the total annual revenue and total cost (RMB) from hog sales in 2018? (Please estimate if you do not know the exact figure.)

Total revenue ____________

Total cost _____________

7. With whom do you discuss hog health? Please write down their names *(note, in the print out more rows were provided)*

Hog farmers

8. From the hog farmers that you listed above, please continue with the Top 3 (most important) for each category and indicate what best describes your relationship with them.

Hog farmers State Name and location of top 3		Acquaintance	Friend or kinship	Good friend or kinship (relative)	A close friend or kinship (relative)
Name	Location				

In the following we are using the term genomics / genomic information. A genome is the full complement of genetic material encoded in the DNA of any living thing. It can be described as a "blueprint" for an organism's structure and function. Genomics is the science that aims to decipher and understand the entire genetic information of an organism encoded in its DNA, for example, in a pig. Among others, using genomics could be a way to stop the spread of animal diseases.

9. Assuming the costs are the same, would you be interested in purchasing semen made using genomics that have demonstrated resistance to African Swine fever (ASF)?

Yes______ No______

If YES, how soon would you adopt this technology when it is made commercially available?

Immediately	After 1 year	After 2 years	After 5 years	After 10 years

10. The latest research shows that the use of genomic information in breeding could reduce the incidence of ASF. Given this information, please indicate your likelihood of adopting this technology given the below reduction of ASF in %.

ASF reduced by	Definitely Not (1)	(2)	(3)	(4)	Definitely (5)
0%-19%					
20%-39%					
40%-59%					
60%-79%					
80%-100%					

11. Please indicate how important the following aspects are to you in adopting the use of genomic information for the selection of African Swine Fever (ASF) resistant hogs on your farm

	Very Unimportant (1)	(2)	(3)	(4)	Very Important (5)
Contributes to the protection of resources for future generations					
Ensures the production of safe products					
Ensures competitiveness of your farm					
Does not require additional training					
The technology can be tested with small batches of animals on the farm first					
Is compatible with the values of society and consumers					
Does not increase problems such as inbreeding and increased susceptibility to other diseases					
Is not linked to a high risk of malfunctioning (reliability)					
Does not increase work load					
Does not increase time spending on disease controlling					
Enables cost neutrality or even cost reduction					
High accuracy on breeding values					

APPENDIX F

CHOICES IN THE LOTTERY

	Option A		Option B
(1)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 0 for sure
(2)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 50 for sure
(3)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 100 for sure
(4)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 150 for sure
(5)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 200 for sure
(6)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 250 for sure
(7)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 300 for sure
(8)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 350 for sure
(9)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 400 for sure
(10)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 450 for sure
(11)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 500 for sure
(12)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 550 for sure
(13)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 600 for sure
(14)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 650 for sure
(15)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 700 for sure
(16)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 750 for sure
(17)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 800 for sure
(18)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 850 for sure
(19)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 900 for sure
(20)	50% chance of winning ¥1,500 and 50% chance of winning ¥0	or	¥ 950 for sure

APPENDIX G

CORE/PERIPHERY RESULTS

Results for hog farmers in G County	
Core	G1, G3, G9, G10
Periphery	G2, G8, G6, G7, G5, G4, G11, L5
Results for hog farmers in L County	
Core	L1, L3, L5, L7, L8
Periphery	L2, L4, L6, L9, L10, G3
Results for hog farmers in S County	
Core	S3, S6, S7
Periphery	S1, S2, S8, S5, S4, S9, S11
Results for hog farmers in Hebei Province	
Core	H3 H4 H6
Periphery	H1, H2, H5, H7, H8, H9, H10, H11, H12, H13, H14

APPENDIX H

CENTRALITY MEASUREMENTS OF FARMERS IN G COUNTRY

Name	Freeman's Degree	*n* Closeness	*n* Betweenness
G1	3.00	44.00	21.52
G2	3.00	44.00	27.88
G3	3.00	37.93	18.18
G4	2.00	40.74	15.46
G5	1.00	32.35	0.00
G6	2.00	45.83	26.67
G7	4.00	45.83	40.30
G8	1.00	32.35	0.00
L4	1.00	28.21	0.00
G9	3.00	42.31	6.67
G10	4.00	50.00	36.06
G11	1.00	31.43	0.00
Mean		39.58	16.06
Std Dev		6.69	14.13
Sum		474.99	192.73
Variance		44.81	199.54
Minimum		28.21	0
Maximum		50	40.30
NCI		23.87%	26.45%

APPENDIX I

CENTRALITY MEASUREMENTS OF FARMERS IN L COUNTY

Name	Freeman's Degree	*n* Closeness	*n* Betweenness
L1	3.00	16.13	8.89
L2	1.00	15.15	0.00
L3	2.00	15.63	1.11
L4	2.00	15.63	1.11
L5	2.00	11.11	2.22
G3	1.00	10.99	0.00
L6	1.00	10.99	0.00
L7	3.00	16.13	5.56
L8	3.00	16.13	5.56
L9	0.00	0	0.00
L10	0.00	0	0.00
Mean		14.21	2.22
Std Dev		2.27	2.92
Sum		127.88	24.44
Variance		5.14	8.53
Minimum		10.99	0.00
Maximum		16.13	8.89
NCI			7.33%

APPENDIX J

CENTRALITY MEASUREMENTS OF FARMERS IN S COUNTRY

Name	Freeman's Degree	*n* Closeness	*n* Betweenness
S1	2.00	50.00	55.56
S2	3.00	47.62	53.33
S3	3.00	35.71	0.00
S4	2.00	34.48	0.00
S5	4.00	37.04	2.22
S6	3.00	35.71	0.00
S7	5.00	47.62	55.56
S8	4.00	40.00	15.56
S9	3.00	31.25	0.00
S10	4.00	40.00	15.56
S11	3.00	31.25	0.00
Mean		39.15	17.98
Std Dev		6.31	23.26
Sum		430.69	197.78
Variance		39.75	540.92
Minimum		31.25	0.00
Maximum		50.00	55.56
NCI		25.19%	41.33%

APPENDIX K

CENTRALITY MEASUREMENTS OF FARMERS IN HEBEI

Name	Freeman's Degree	*n* Closeness	*n* Betweenness
H1	4.00	48.15	22.22
H2	2.00	44.83	6.85
H3	3.00	43.33	5.79
H4	4.00	43.33	10.94
H5	5.00	59.09	44.43
H6	3.00	37.14	0.43
H7	2.00	38.24	15.39
H8	3.00	43.33	5.79
H9	4.00	54.17	38.41
H10	1.00	33.33	0.00
H11	1.00	28.26	0.00
H12	3.00	37.14	0.86
H13	3.00	44.83	6.83
H14	4.00	43.33	7.45
Mean		42.75	11.81
Std Dev	.	7.65	13.53
Sum		589.51	165.39
Variance		58.46	183.08
Minimum		28.26	0.00
Maximum		59.09	44.43
NCI		36.66%	35.13%

APPENDIX L

MEAN-DIFFERENCE TEST RESULTS

	No. of farmers	Differences in means
Genomics technology adoption		
Likelihood to adopt semen with genomics traits	42	-0.13
Adoption rate when the technology could reduce the ASF by 40%-59%	42	-0.06
Adoption rate when the technology could reduce the ASF by 60%-79%	42	0.06
Adoption rate when the technology could reduce the ASF by 80%-100%	42	-0.15
Risk preference		
Lottery risk preference	42	-0.17

APPENDIX M

SURVEY QUESTIONS

Note: Participants received a version translated to Chinese.

1. Are you: male _____ female____

2. How old are you? ____ years

3. What is the highest level of education that you have obtained?

Elementary school or below _____
Middle school_____
High school_____
College degree_____
Undergraduate or above_____

4. Which of the following best describes your operation in 2019?

Farrow-to-finish_____
Farrow-to-wean_____
Feeder_____
Breeding stock_____
Company & Producers_____

5. Including 2019, for how many years have you been raising hogs? ______ years

6. What was the total annual revenue and total cost (RMB) from hog sales in 2018? (Please estimate if you do not know the exact figure.)

Total revenue ____________
Total cost _____________

7. With whom do you discuss hog health? Please write down their names *(note, in the print out more rows were provided)*

Hog producers	Veterinarian	Sales agents

8. From the hog producers, veterinarians and sales agents that you listed above, please continue with the Top 3 (most important) for each category and indicate what best describes your relationship with them.

Hog producers State Name and location of top 3		Acquaintance	Friend or kinship	Good friend or kinship (relative)	A close friend or kinship (relative)
Name	Location				

Veterinarians State Name and location of top 3		Acquaintance	Friend or kinship	Good friend or kinship (relative)	A close friend or kinship (relative)
Name	Location				

Sales agents State Name and location of top 3		Acquaintance	Friend or kinship	Good friend or kinship (relative)	A close friend or kinship (relative)
Name	Location				

9. Please indicate how often on average you were / are in contact with the 3 most important individuals that you just wrote down before and after the African Swine Fever (ASF) outbreak in 2018. You may have more than one way to contact each of them. Please indicate how you communicate with them. Please make sure to write down their name.

Hog producers

1) Hog producer — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

2) Hog producer — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling						

	e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

3) Hog producer — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

Veterinarians

1) Veterinarian — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

2) Veterinarian — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily

Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						
3) Veterinarian — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

Sales agents

1) Sales agent — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						

Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

2) Sales agent — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

3) Sales agent — Write Name:		Less than monthly	Monthly	A few times a month	Weekly	A few times a week	Daily
Before ASF	Social network text (We Chat, etc.)						
After ASF	Social network text (We Chat, etc.)						
Before ASF	Phone call/Online calling e.g. Video chat						
After ASF	Phone call/Online calling						

	e.g. Video chat						
Before ASF	Meeting face to face						
After ASF	Meeting face-to-face						

APPENDIX N

PERMISSION LETTERS

W. P. Carey School of Business
Arizona State University

To:
Shijun Gao

November 7, 2022

Dear Shijun Gao.

I am writing to grant you permission to use the article on which I am a co-author in your dissertation. The reference to the article is below.

Gao, S., C. Grebitus, and T.G. Schmitz. 2022. "Effects of Risk Preferences and Peer Influence on Adoption of Genomics by Chinese Hog Farmers." *Journal of Rural Studies* 94:111–127.

Title of the article: Effects of Risk Preferences and Peer Influence on Adoption of Genomics by Chinese Hog Farmers

Authors of the article: Gao, Shijun; Grebitus, Carola, and Schmitz, Troy G.

Periodical Title: *Journal of Rural Studies*

Volume: 94, Pages: 111-127

This request grants permission to Shijun Gao to include the content of the above-mentioned article in his dissertation, here at the Arizona State University. With this permission, the article can be included in the dissertation, whether in full or in part and submitted to the university's repository in either print or electronic form.

If you have any questions, please feel free to contact me at carola.grebitus@asu.edu.

Sincerely,

Carola Grebitus

Dr. Carola Grebitus
Associate Professor of Food Industry Management
Dean's Council of 100 Distinguished Scholar
Morrison School of Agribusiness
W. P. Carey School of Business
Arizona State University

Morrison School of Agribusiness
7231 E. Sonoran Arroyo Mall, Santan Hall, Suite #230, Mesa, AZ 85212
p: 480-727-1566 **f:** 480-727-1961 **email:** wpcarey.Morrison@asu.edu **web:** www.wpcarey.asu.edu

W. P. Carey
School of Business
Arizona State University

To:
Shijun Gao

November 8, 2022

Dear Shijun Gao.

I am writing to grant you permission to use the article on which I am a co-author in your dissertation. The reference to the article is below.

Gao, S., C. Grebitus, and T.G. Schmitz. 2022. "Effects of Risk Preferences and Peer Influence on Adoption of Genomics by Chinese Hog Farmers." *Journal of Rural Studies* 94:111–127.

Title of the article: Effects of Risk Preferences and Peer Influence on Adoption of Genomics by Chinese Hog Farmers

Authors of the article: Gao, Shijun; Grebitus, Carola, and Schmitz, Troy G.

Periodical Title: *Journal of Rural Studies*

Volume: 94, Pages: 111-127

This request grants permission to Shijun Gao to include the content of the above-mentioned article in his dissertation, here at the Arizona State University. With this permission, the article can be included in the dissertation, whether in full or in part and submitted to the university's repository in either print or electronic form.

If you have any questions, please feel free to contact me at troy.schmitz@asu.edu.

Sincerely,

Dr. Troy G. Schmitz
Director and Professor
Morrison School of Agribusiness
W. P. Carey School of Business
Arizona State University

Morrison School of Agribusiness
7231 E. Sonoran Arroyo Mall, Santan Hall, Suite #230, Mesa, AZ 85212
p: 480-727-1586 **f:** 480-727-1961 **email:** wpcarey.Morrison@asu.edu **web:** www.wpcarey.asu.edu

APPENDIX O

IRB APPROVAL LETTERS

EXEMPTION GRANTED

Carola Grebitus
WPC: Agribusiness, Morrison School of
480/727-4098
Carola.Grebitus@asu.edu

Dear Carola Grebitus:

On 5/12/2021 the ASU IRB reviewed the following protocol:

Type of Review:	Modification / Update
Title:	Strengthening U.S. Beef Export Markets: Analysis of Consumer Willingness to Pay and Import Demand
Investigator:	Carola Grebitus
IRB ID:	STUDY00011924
Funding:	Name: USDA: National Institute of Food and Agriculture (NIFA), Grant Office ID: FP00020317, Funding Source ID: GRANT12907247
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• China Spring Survey, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Chinese survey, Category: Translations; • Pre-test consent form , Category: Consent Form; • Protocol updated, Category: IRB Protocol; • translated consent form, Category: Consent Form; • translation certificate, Category: Other;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 5/12/2021.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

EXEMPTION GRANTED

Carola Grebitus
WPC: Agribusiness, Morrison School of
480/727-4098
Carola.Grebitus@asu.edu

Dear Carola Grebitus:

On 7/16/2019 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Effects of Social Networks on Acceptance of Genomics for Hog Breeding in China
Investigator:	Carola Grebitus
IRB ID:	STUDY00010398
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• recruit, Category: Recruitment Materials; • survey, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Protocol , Category: IRB Protocol; • consent, Category: Consent Form;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 7/16/2019.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator