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Three essays on job satisfaction, meat consumption and transgenic soybean

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

To those who provided me the strongest support in completing this dissertation

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ABSTRACT

This dissertation is to study the issues of Chinese worker's job satisfaction, Chinese consumer's meat consumption pattern change, and the potential economic effect of adopting Sudden Death Syndrome (SDS) resistant soybean in the U.S. In Chapter 1, we use a Mincer earnings function to generate expected wages for each worker based on their skills and region, and use the unexplained wage as the objective measure of treatment to study how the objective measures based on these would affect Chinese worker's perceptions concerning employment. We find that the observed and the unexplained wage positively affect job satisfaction, promotion satisfaction and social status. The effects of income inequality on the three employment perception measures depend on their observabilities. Holding unexpected wage constant, old workers have higher level of job satisfaction and social status than their young counterparts; old, female, rural and educated workers have higher level of job satisfaction and social status; old, female and rural workers report higher level of promotion satisfaction. Finally, workers in government departments have the highest level of the three employment perception measures. In Chapter 2, we apply a censored demand system approach with an Almost Ideal Demand System specification to study what Chinese consumer's meat consumption patterns were like and how it changed over time, across provinces or across income groups. We find that as household income increases, meat expenditures increase, with pork capturing a larger share. The general pattern for elasticities holds across both provinces and income groups. Pork and other meats are necessities while beef, mutton and chicken are luxury goods. The pattern change of meat consumption in China implies a great opportunity for U.S. pork export growth if China removes retaliatory duties imposed on U.S. pork exports in the background of U.S.-China trade war. In Chapter 3, we adopt a crop sector model to study the potential economic impacts if the SDS resistant soybean variety was adopted historically.

We find that if SDS resistant soybean variety was adopted in history, total equilibrium supply would have increased by 0.1%-0.5% from 2000-2017, and soybean price would have decreased by 0.1%; crush, export and stocks would have decreased by 0-0.2%, increased by 0.1%-0.4%, and increased by 0.1%-3.8%. Adoption of SDS resistant transgenic soybean variety would have brought larger benefits to producers than consumers in general, and producer benefits would have peaked in the years with the largest outbreaks of SDS.

CHAPTER 1. GENERAL INTRODUCTION

As time goes on, international trades and co-operations are taking place much more frequently than before, and the whole world's economy is becoming an increasingly compact system. In recent decades, China experienced rapid economic growth and has grown into the second largest economy in the whole world, while the United States remained the largest. Between the largest and the second largest economies, many interesting issues began to draw comprehensive attention and deserve investigation.

Job satisfaction was previously an important topic in psychology. In recent decades, it was studied more and more by economists, and have become increasingly popular in Economics. Job satisfaction is very important because it is not only a good indicator of personal well-being, but also has much influence on job turnover rate, which further impacts a firm's incentive to foster an employee's skills for the job and hence influences the firm's productivity. As China has grown into the world's second largest economy, the wage inequality has also increased over decades in China. Although many studies concerning job satisfaction have been done in developed countries like the United States, Britain or Germany, whether the case is the same in China and if wage inequality plays a role in determining Chinese worker's job satisfaction are still unknown.

In the background of the trade war between China and the United States beginning from 2018, topics concerning the trade war become increasingly popular and have been drawing public attention. In the trade war, China imposed retaliatory levies on U.S. exports in response to the U.S. actions. In July 2018, China imposed 25% tariff on both U.S. pork and soybeans, and a further 10% on pork as well as a 5% on soybeans in September 2019. After a long process of negotiation, an agreement was reached between the two countries that China would waive the tariff on U.S.

pork and soybean export. This agreement would be likely to bring much benefits and great opportunities to pork production and soybean industry in the United States. Hence, it would be useful to have a most recent estimation of Chinese consumers' meat demand as well as soybean production in the United States.

This dissertation is to address those questions. In Chapter 2, we investigate Chinese worker's job satisfaction, promotion satisfaction and social status. We run a regression on Mincer Earnings Function, and create four objective measures of treatment, relative income and wage inequality based on this regression. Then, we run another regression on Chinese worker's employment perception measures of job satisfaction, promotion satisfaction and social status using the four objective measures as well as demographic variables. From the second regression, we can know how the objective measures will affect Chinese workers' employment perceptions and whether the case in China is similar to those cases in developed countries. In Chapter 3, we study Chinese consumer's meat consumption patterns and their changes. We investigate the consumption pattern of five different kinds of meat: pork, beef, mutton, chicken and other meats. A censored demand system approach using an Almost Ideal Demand System (AIDS model) is applied for running regressions on each kind of meat; and we estimate the corresponding elasticities, including income elasticities, Marshallian price elasticities and Hicksian price elasticities based on these regressions. The elasticities estimation will reveal the meat consumption patterns and their changes over time. In Chapter 4, we study the economic effects of adopting Sudden Death Syndrome (SDS) resistant transgenic soybean. We set up a global partial equilibrium model and develop two scenarios to study the impacts of adopting SDS resistant soybean on price, supply, crush, export and ending stocks. Also, we investigate the welfare effects that the adoption of SDS resistant soybean brings to the producers and the consumers.

CHAPTER 2. WAGE INFORMATION, JOB SATISFACTION, AND PERCEIVED SOCIAL STATUS IN CHINA

Abstract

The 2014 edition of the China Family Panel Studies dataset is used to show how perceptions of job satisfaction, promotion satisfaction and social status vary based on individual treatment in the labor market. A Mincer Earnings Function is used to generate expected wages for each worker based on his or her education, work experience, and region. The unexplained wage-the difference between actual and expected wages-is a measure of the individual worker's treatment. Workers paid less than expected based on their skills are considered to be treated relatively poorly while those paid more than expected are treated atypically well.

Similar to studies based on market economies, Chinese perceptions of job satisfaction, promotion satisfaction and social status are nearly uncorrelated with market information. Both observed and unexplained higher individual wage relative to the expected market wage positively affects the three employment perception measures, and the effects of income inequality differ by its observability; holding the unexpected wage constant, old workers are more inclined to report higher level of job satisfaction and social status than their young counterparts, and the old, female, rural and educated workers experience higher level of job satisfaction and social status, and the old, female and rural workers report higher level of promotion satisfaction. Workers in government departments report the highest level of job satisfaction, promotion satisfaction and social status.

Keywords: job satisfaction, social status, treatment, Mincer Earnings Function

Introduction

Job satisfaction is an important indicator of personal well-being. More satisfied workers may be more productive. Higher job satisfaction may diminish job turnover, preserving firm-specific skills. Lower turnover may also increase the firm's incentive to invest in worker training. Most of the research on job satisfaction has focused on market economies. However, over the past 20 years as the Chinese economy has grown into the world's second largest economy, wage inequality, migration, wages and benefits have become increasingly important. We will investigate how worker satisfaction in China has been affected by these factors.

Past work on job satisfaction in China has ignored the role of income inequality. Inequality has increased significantly, as documented by Chen Wang, Guanghua Wan, and Dan Yang (2014). As shown in Figure 1, China's overall Gini Coefficient increased from 0.28 in 1983 to a high of 0.50 in 2007. Since then, the Gini Coefficient has decreased slightly 0.47 by 2013. Income inequality has also increased across regions in China. Dennis Tao Yang (1999) used household survey data from China's State Statistical Bureau to investigate the sources and causes of the rising inequality. He found that increases in rural-urban income differentials had been the driving factor behind the rising overall inequality in China. Martin Ravallion and Shaohua Chen (2007) also studied the trend of China's urban-rural income gap over the two decades. They showed that income gap between urban and rural areas of China generally increased as time went on, especially in the years from 1997-2002. Terry Sicular, Yue Ximing, Björn Gustafsson and Li Shi (2007) also found large urban-rural income gaps that increased slightly over time, even after controlling for demographic and migratory changes and for spatial prices.

China's gender wage gap has also been increasing. Björn Gustafsson and Li Shi(2000) analyzed China's gender wage gap and its development in urban areas using large scale surveys covering data from 10 provinces for 1988-1995. They found that, while China's gender wage gap is relatively small from an international perspective, it had been increasing. Wei Chi and Bo Li (2014) studied the trends in China's gender employment and wage gaps over the 1988 – 2009 period. Over the 20 years, both men and women's earnings increased significantly. However, the gender pay gap also increased from 0.2 to 0.35 log points by 2009. They also studied the gender employment gap as well as their influences at different levels of education. They concluded that the employment gap between male and female workers increased since 2005 as female employment rate had been falling, and the enlarged gender employment gap increased the extent of the underestimation of the raw gender pay gap.

Wage gaps between ethnic groups have also widened over the decades. Since China's major ethnic group, the *Han*, consists of approximately 91% of the total population and the other 55 minor ethnic groups consist of 9% of the population in total, studies are typically done between the majority *Han* and the aggregate of the minorities. Björn Gustafsson and Li Shi (2003) found that although the average earnings of the minorities increased during 1988-1995 under the analysis, the growth was much slower than that of the majority. They also concluded that the growing earnings gap was due to different geographical distributions of the majority and the minorities. Margaret Maurer-Fazio, James Hughes and Dandan Zhang (2010) used data collected from three China population censuses to investigate the differences in the labor force participation rates of China's important ethnic groups. Sizable differences were found between the labor force participation rates of prime-aged urban *Han* women and women from some other particular ethnic groups.

These papers show that the long period of economic growth in China since 1980 has been accompanied by rising inequality overall, and rising income gaps between provinces, between urban and rural residents, between men and women, between education groups, and between majority and minority groups. However, do workers in China really know about these inequalities and gaps, and do the gaps affect satisfaction with compensation and employment?

In recent years, increasing numbers of studies looked into the deviations between the perceived income inequality and the actual inequality, and further investigated their influences on people's behaviors. Vladimir Gimpelson and Daniel Treisman (2018) found that ordinary people usually misperceive the actual income inequality; and it was the perceived inequality, rather than the actual inequality, that had a strong correlation with the demand for redistribution. Carina Engelhardt and Andreas Wagener (2014) found that there was a positive link between the extent of redistribution in democratic regimes and perceived inequality, rather than the objective measures of inequality. So given the fact that China's income inequality actually increased over the decades, does the objective information concerning inequalities and gaps in China actually affect Chinese worker's level of job satisfaction?

While academic papers written in English are not accessible to the average Chinese workers, there are other ways for workers to obtain information concerning inequality and wages. The Chinese government has released information on average employment and wages by province through the National Bureau of Statistics of People's Republic of China since 1991. This information does make its way to the public through media outlets. The State Council Information Office of the People's Republic of China and China's News Network have reported on the Gini coefficient since 2003. It is not clear whether workers absorb the information. Moreover, the media is controlled by the government, and so not all relevant information may be forthcoming.

This study will explore whether Chinese worker's job satisfaction is affected by objective measures of income inequality, and how the level of job satisfaction varies across different demograhic groups in the Chinese workforce. To do this, we need to first establish objective measures of wage distributions in China. For each individual worker, we develop a measure of the fair market wage based on his or her skills. We can then measure the deviation between the actual wage relative to the fair market wage. That deviation will measure whether the individual is being treated atypically well or atypically badly by the labor market. We can also measure these pay discrepancies at the provincial level to see if workers in the area are treated atypically well or atypically badly. We measure the worker's relative position in the wage distribution using the ratio of each individual's income relative to the provincial average. Finally, we can measure the variance of the unexplained variation in pay at the provincial level as a measure of the actual income inequality among similar workers in the local labor market, and the 80^{th} to 20^{th} percentile ratio of individual income by province as a measure of the observable income inequality. These objective measures of how the worker has been treated by the market will be compared against worker perceptions of job satisfaction. From our results, we found that all the perception measures of Job Satisfaction, Promotion Satisfaction and Social Status are positively affected by higher individual wage relative to their expected market wage, regardless of its observability. Holding unexpected wage constant, old workers experience higher job satisfation and social status; old, female, rural and educated workers experience higher level of job satisfaction and social status, while old, female and rural workers have higher level of promotion satisfaction. Finally, we found that workers in government departments have the highest level in all the three employment perception measures.

Literature Review

Job satisfaction as an indicator of personal well-being has been examined extensively in western labor markets. Jose Maria Millán, Jolanda Hessels, Roy Thurik and Rafael Aguado (2013) used data from the European Community Household Panel (ECHP) covering 1994-2001 to show that self-reported job satisfaction for both self-employed individuals and paid employees increases with income growth and falls with unemployment spells. Using the same data, Joern H. Block, Jose Maria Millán, Concepcion Román and Haibo Zhou (2015) showed that family employees have higher level of job satisfaction but lower wages relative to other employees, suggesting that workers are willing to tradeoff wages for better working conditions. In both studies, job satisfaction rises with education. Felix FitzRoy and Michael Nolan (2017) used the British Household Panel Survey data to study life satisfaction as opposed to job satisfaction. They found that the highly educated have been gaining in life satisfaction over time while older and less-educated individuals have been experiencing declining life satisfaction. Wenshu Gao and Russell Smyth (2010) examined job satisfaction in two Chinese data sets, one limited to workers in 78 firms in Shanghai and another looking at workers in 6 different Chinese cities. They found that in the Shanghai sample, higher individual income relative to the firm average raises job satisfaction. In the six-city sample, higher income relative to the reference wage for similarly skilled workers also raises job satisfaction.

Related studies have examined Chinese worker's labor turnover. Wenshu Gao and Russell Smyth (2010), investigated how urban Chinese worker's job satisfaction was affected by an increase in a reference group's income. They named that workers are jealous about the reference group's income increase as a status effect, which lowers individual job satisfaction; and that an increase in the reference group's income signals individual future prospects as a signal effect, which increases individual job satisfaction. They found that if they used a single item indicator there were no support for a status or signal effect; however, if they use a psychometrically valid instrument to measure job satisfaction, they found the existence of a status effect. Ting-Pang Huang (2011) compared the motivating work characteristics, job satisfaction and turnover intentions of knowledge workers and blue-collar workers in both China and Japan. They found that in both countries, knowledge workers had significantly higher motivational work characteristics, however, Japanese knowledge workers only showed marginally higher job satisfaction than their blue-collar counterparts while Chinese knowledge workers showed marginally lower job satisfaction than the blue-collar workers in China. And there was no significant difference between the turnover intention of Japanese knowledge workers and Chinese knowledge workers. John Knight and Linda Yueh (2004) analyzed the inter-firm mobility of labor force in China's urban labor market. They distinguished the difference between urban residents and rural-urban migrants, and found that the firm turnover rate of migrants significantly exceeds that of urban residents.

Background

The 2014 China Family Panel Studies (CFPS) provides a nationally representative sample of the Chinese workforce.[1]The survey elicits information from 37,147 respondents on their perceptions of their own pay, their status in society, and the level of job satisfaction as well as promotion satisfaction in the labor market. The questions that will represent our dependent variables in this study are presented in Table 1. The first question reflects the respondent's self rating of job satisfaction, indicating the level of job satisfaction from very low to very high. A

[1] The survey is administered by the Institute of Social Science Survey(ISSS) at Peking University.

second question elicits the respondent's rating of promotion satisfaction, which is also a question relevant to job satisfaction. The third question asks the respondent's belief about their self-perceived *Social status* from low to high. Note that the three dependent variables, *Job Satisfaction*, *Promotion Satisfaction* and *Social Status,* are represented by numbers from 1 to 5. The translated questions are reported in Table 1.

To get a sense of the variation in these assessments of job satisfaction, promotion satisfaction or social status in the labor market, we compare these assessments between older (≥ 60) and younger (<35) workers; between men and women; between urban and rural residents; between more educated (at least a Bacherlor's Degree) and less educated (primary educated or less); and between *Han* and minority workers. Reported t-statistics test whether the differences in the means between the groups are statistically significant. There are some clear differences between demographic groups in assessments about the importance of job satisfaction or social status in the Chinese economy.

As is shown, old workers are significantly happier with their jobs, and they perceived their social status as higher than their younger counterparts. There is not much difference in the level of job satisfaction and social status between men and women workers. Rural workers expressed similar level of job satisfaction as urban workers, but report significantly higher social status. Educated workers have a higher level of job satisfaction but lower social status than less educated workers. *Han* workers have much higher level of job satisfaction than minorities, but they have lower perception of social status than do minority workers. There is no significant difference between the demographic groups in promotion satisfaction.

Perceptions of job satisfaction in Table 2 differ most by age, education levels and ethnicity, and much less by gender and location. Social status differs most by age, location, education and ethnicty, and less by gender. We have two interesting findings that the old workers have higher levels of job satisfaction and perceived social status, and the educated workers perceived higher job satisfaction but lower social status. The first finding seems to be a puzzle because we can see from Figure 1 that in the past decades from 1983-2007, China's income inequality kept rising to its maximum level, and plateaued afterwards. In the period 1983-2007, the oldest workers would have experienced the complete period of rising income inequality. And yet, the old workers are more satisfied with their jobs and profess higher social status than the youngest workers who would have entered an already unequal labor market. Nevertheless, this finding is consistent with past studies. Andrew Clark (2003) found a significant and positive correlation between well-being and reference group income inequality in the British case, and Johannes Schwarze and Macro Härpfer (2004) found no significant evidence that the Germans were inequality averse.

The second finding that the educated workers having higher job satisfaction is consistent with the British case of Felix FitzRoy and Michael Nolan (2017). They found higher education was associated with higher level of life satisfaction. However, we found the most educated had lower perception of social status than did the less educated. Evans W. Curry and Derald Walling (1984) pointed out that education and income both contributed to occupational prestige, but education relies on income as a necessary condition to its impact on prestige. In our sampleLater, we will show that less educated workers are more likely to be paid more tha the fair market rate, and that wage premium affects their higher perceived social statis.

In the next section, we develop measures of personal-level and labor market-level indicators of personal treatment, inequality and relative income using available information on wages in each individual's local labor market. These form the objective basis for perceptions of job satisfaction and social status. We can then test the extent to which Chinese worker perceptions of job satisfaction and social status are based on these objective measures or whether these perceptions are not tied to actual local labor market outcomes.

Methodology

Our aim is to assess whether Chinese workers' perceptions of job satisfaction and social status are shaped by objective information on market wages. To accomplish that, we need to propose plausible measures of objectively based perceptions of fair wages.

James S.Duesenberry (1949) proposed that notions of fairness and perceived social status were shaped by relative income, defined as the comparison between one's own income level and the average income level in the labor market. Other studies have associated relative income with status (George Kosicki,1987); subjective well-being (Michael McBride, 2001; De La Garza et al, 2010); satisfaction with pay (Michelle Brown, 2001); or with job satisfaction(Rodrigo Montero and Diego Vasquez, 2015).

A second measure of own wages relative to market norms is based on the own wages compared to the wages paid to workers with comparable skills. Daniel S. Hamermesh (1977) used individual wages realtive to the wage predicted by individual skills in his study of job satisfaction. Andrew E. Clark and Andrew J. Oswald (1996) treated the wage predicted on the basis of individual skills as a measure of the 'fair wage'. In recent years, Alasdair Rutherford (2009) and Temesgen Kifle (2014) also used similar measures of 'fair wage' predicted on individual skills. The strategies of these studies applied extensions of the log earnings function developed by Jacob Mincer (1974), a strategy we also use. Consider the following form of the Mincer Earnings function with regional dummy variables used to control for variation in local cost of living:

$$\ln W_{ij} = \beta_0 + \beta_S S_{ij} + \beta_x x_{ij} + \beta_{x2} x_{ij}^2 + \sum_{j=1}^{J} \theta_j D_j + \varepsilon_{ij}, \varepsilon_{ij} \sim \mathcal{N}\left(0, \sigma_j^{\ 2}\right) \tag{1}$$ [1]

where $\ln W_{ij}$ is the log wage for the i^{th} worker in province j; S_{ij} is years of schooling; x_{ij} is years of work experience; D_j is a regional dummy variable; and θ_j is the coefficient measuring relative cost of living and other factors affecting relative wage levels across regions. The fitted values of our Mincer Earnings function predicts how much an individual "should" earn based on observable skills and other demographic attributes which can be taken as a "fair" wage. Deviations between actual and predicted wages will indicate if the worker is paid above or below this "fair" wage, $\varepsilon_{ij} = \ln W_{ij} - \ln \hat{W}_{ij}$. Higher values of this residual were used by Daniel S. Hamermesh (1977), Andrew E. Clark and Andrew J. Oswald (1996), Alasdair Rutherford (2009) and Temesgen Kifle (2014) to explain job satisfaction.

The level of inequality in the local market can be estimated as $\sigma_j^2 = Var(\varepsilon_{ij} \mid j)$, the variance of ε_{ij} in each province j. Sherman Robinson (1976), Daniel S. Hamermesh (1977), John B. Knight and Richard H. Sabot (1983), and George A. Akerlof and Janet L. Yellen (1988) used the variance of wages as a measure of the extent of income inequality. Our use of the error variance as a measure of inequality measures the variability in earnings for workers with the same observable skills. Thomas Lemieux (2006) , Chunbing Xing and Shi Li (2012), and Pravin Krishna, Jennifer P. Poole and Mine Zeynep Senses (2012) also used the variance of the error term from the estimation of a wage equation as a measure of income inequality. Even if workers would

[1] We use the basic form of the Mincer Earnings function from Jacob Mincer (1974) that have been proved the return to schooling follows a linear form while the return to experience follows a quadratic form.

not literally observe the error terms or the error variance, they may intuit whether their wage is fair or the degree of inequality among equivalent workers.

However, they are more likely to observe average wages and inequality in their local markets. Consequently, we consider measures that would more closely match the Duesenberry (1949) measure of relative income, which was also used by Ekkehart Schlicht (1978) and Laetitia Hauret and Donald R. Williams (2017). We measure the individual's relative income by $\frac{W_{ij}}{W_j}$, the ratio of individual wage relative to the provincial average. Following Peter Gottschalk and Timothy M. Smeeding (1997), Orlando J. Sotomayor (2004), Karsten Kohn and Dirk Antonczyk (2011), and David Card, Jörg Heining and Patrick Kline (2013), we use the ratio of the 80th percentile wage to the 20th percentile wage in the province as our observable measure of inequality, $\frac{W_j^{80}}{W_j^{20}}$. These objective measures of individual and market inequality can be introduced into a model explaining perceptions of job satisfaction, promotion satisfaction or social status, P_{ij}:

$$P_{ij} = \alpha_0 + \alpha_\varepsilon \varepsilon_{ij} + \alpha_\sigma \sigma_j^2 + \alpha_R \frac{W_{ij}}{W_j} + \alpha_{80} \frac{W_j^{80}}{W_j^{20}} + Z_{ij}^{'} \gamma_Z + e_j \qquad (2)$$

where Z_{ij} is a vector of personal attributes that may also influence worker's perceptions of job satisfaction, promotion satisfaction or personal social status. We can test jointly the extent to which perceptions are based on objective information using the parameter estimates on the first four variables, the extent that they vary by demographic attributes using the estimates of γ_Z, and the extent to which they are based on random perceptions, e_j.

Data Details and Sample Statistics

We present estimates of equation (1) based on the 2014 CFPS data in Table 3. The model explains 20% of the variation in log wages. Shanghai is the reference province and so the coefficient on “j-Shanghai” measures the average wage change between the *jth* province and Shanghai. The parameters are typical of Mincerian earnings functions, which means the returns to human capital in China mimics the returns in other countries.

The coefficient on years of schooling implies an 18.4% return from an additional year of education. The coefficients on years of work experiences imply a quadratic relationship with wages peaking at 39 years of experiences. The coefficient of the interaction term of schooling and work experiences is negative, suggesting a modest decrease in returns to schooling as work experience increases. The coefficient implies that ten additional years of experience reduces returns to schooling by about 4%. Since the average work experience is 25.2 years, we can see that an additional year of schooling will increase the return in log wages by 8.3% in total on average. Combined with the average schooling of 8years and the legal age of 6 to attend school as well as the legal age of 16 to work, we can see that all through their career, workers get increasing returns to wages until the age of 55 on average. That probably contributes to the higher job satisfaction and social status of the old workers than the young. In terms of the provincial dummy variables, we excluded Shanghai and used it as the reference region. We can see that the coefficients of the provincial dummies are all negative, revealing that holding other things constant, the returns to log wages is higher in Shanghai than elsewhere.

In Table 4, we present the distribution of the four objective measures of relative wages and market wage inequality based on the 2014 CFPS dataset and our estimate of equation (1). We report the values of these measures by various demographic groups along with tests of the differences in means across groups. There are apparent differences in relative wages between the old workers and the young workers. Old workers have a positive value 0.56 of ε_{ij}, which suggests that they are overpaid compared to their expected wage based on their skills. Meanwhile,young workers are almost paid their expected wage on average so the average error in their wages is only 0.07. The relative wage $\frac{W_{ij}}{\overline{\overline{W}}_j}$ indicates that the old workers are earning less than the average provincial level while the young workers are earning almost the provincial average. The unobservable indicator of inequality σ_j^2 and the observable one $\frac{W_j^{80}}{W_j^{20}}$ both indicate that there is not much difference in income inequality across the old group and the young group.

Male workers have a positive ε_{ij} while the female workers have a negative one, which shows that male workers are paid more than expected while female workers are paid less. The observed relative wage measure tells the same story.There are no significant differences in the inequality measures σ_j^2 and $\frac{W_j^{80}}{W_j^{20}}$ across genders.

There's no significant difference in the error terms between the urban workers and the rural workers. There is also no significant difference between relative wage or in the error variance. Urban workers are earning above the market average, while rural workers are earning below the average. Measured inequality is significantly lower for urban than rural workers.

Educated workers get underpaid while the uneducated workers are slightly overpaid. However, the observed relative wages favors educated workers by almost 77% that of the uneducated. Both measures of inequality, σ_j^2 and $\frac{W_j^{80}}{W_j^{20}}$ are significantly lower for educated than uneducated workers.

Surprisingly, the measured error terms suggest that the majority "Han" workers are significantly underpaid while the minorities are overpaid. Minority workers also have higher observed relative wages, although the differences are not significant. The unobservable and observable inequality are significantly greater for the minority workers.

The information in Table 4 suggests that there are systematic differences in expected and unexpected pay and measured inequality across demographic groups, consistent with the finding of significant differences in job satisfaction and social status found in Table 2. Next, we will investigate the link between the objective measures of under- or over-payment and inequality and the worker's own level of job satisfaction and perceived social status.

Results

The results of the regressions on worker's perceptions are reported in Table 5. Note that in Table 5, we report the results with only ε_{ij}, σ_j^2, $\frac{W_{ij}}{\overline{W_j}}$ and $\frac{W_j^{80}}{W_j^{20}}$ in column A (the four-objective measures-only model), and report the results with demographic variables in column B (the complete model) to make a comparison. To be consistent with the previous analysis, we choose the respondent's characteristics of Age, Gender, Urban/Rural Identity, Years of Education and the Nature of Employer as the demographic variables. There were too few ethnic minority observations per province to include ethnicity as an additional demographic control variable.

In Table 5, we used three dichotomous dummy variables indicating the nature of employer: the first one is "State-owned enterprise", where 1 means the employer is a state-owned enterprise and 0 otherwise; the second one is "Private-sector firm", where 1 means the employer is a private-sector firm and 0 otherwise; and the third one is "Individuals", where 1 means the worker is self-employed and 0 otherwise. Here we use the "Government", including government branches , institutions, schools or social groups, as the reference employer.

Since the perceptions of job satisfaction, promotion satisfaction and social status are ordinal numbers from 1 to 5, so we follow Andrew E. Clark and Andrew J. Oswald's (1996) strategy evaluating job satisfaction by using Ordered Probit for the estimation. To make the results comparable across the regressions, we report elasticities. The associated z-statistics are reported in the parentheses below the elasticities.

The Likelihood ratio tests $\chi^2(2)$ or $\chi^2(7)$ are used for checking if the group of measures or the demographic variables are jointly significant in the complete model, which are reported below the demographics and above the Pseudo R^2 of model A and B in Table 5. Also, the Pseudo R^2 of the corresponding group of measures are reported under the corresponding χ^2 test, to check the contribution the group of measures make to the explanation of the model.

At first, we take a look at model A with the four objective measures only. In Table 5, we find the observed measures of $\frac{W_{ij}}{\overline{\overline{W}}_j}$ and $\frac{W_j^{80}}{W_j^{20}}$ and the individual measures of ε_{ij} and $\frac{W_{ij}}{\overline{\overline{W}}_j}$ are all jointly significant in explaining all of the perceptions of job satisfaction, promotion satisfaction and social status, while the unobserved measures ε_{ij} and σ_j^2 are not jointly significant in explaining social status, and the market measures of σ_j^2 and $\frac{W_j^{80}}{W_j^{20}}$ are not jointly significant in explaining job satisfaction. At the same time, it is clear that no matter concerning the variation of what perception, the Pseudo R^2 is really small, indicating the factual information of treatment, relative income and inequality as well as demographic attributes only explains no more than 2.2% of the variations in worker's perceptions of job satisfaction, promotion satisfaction and social status.

We can make a comparison with the results of the representative studies of job satisfaction: Alasdair Rutherford (2009), Daniel S. Hamermesh (1999), and Wenshu Gao and Russell Smyth (2010), who used unexplained wage, income inequality and relative income as the determinants of job satisfaction respectively, and studied the cases in the UK, US, Germany and China. The R^2 or R^2 equivalent of their job satisfaction equation are also very small-about 1%~3% in 2004 in the UK, about 3.8% in 1990 and about 5% in 1996 in the US, about 3.4% in 1990 and about 7% in 1996 in Germany, and about 4.5%~7.3% in 1997 and 2007 in China. We can see from the comparison that our value of R^2 is quite consistent to the literature, which means worker's perceptions of job satisfaction, promotion satisfaction and social status are not primarily based on objective information concerning unexplained wage, inequality and relative income, and there are not much differences between the cases of developed countries like the UK, US and Germany, or developing countries like China.

The four objective measures are very important, but as Table 5 shows, they explain only 0.28%~0.57% of the variations in perceptions. So, what are the variations in perceptions related to? Actually the demographic difference matters more. The four objective measures of treatment, inequality and relative income and the demographic variables in total explain about 0.46%~2.2% of the variations in workers' perceptions of job satisfaction, promotion satisfaction and social status, and the parts of the variations in perceptions explained by the models are mostly contributed by the differences in demographic characteristics in marginal contribution. Compared to model A, when demographic control variables are added in model B, they are all jointly significant and contribute 0.0018~0.0164 to the increase in Pseudo R^2.

The effects of the objective measures show that as relative income goes up, all of the perceptions of job satisfaction, promotion satisfaction and social status significantly improve. The effects of income inequality are all zero, because they're not statistically different from zero, no matter for the unobserved inequality measured by σ_j^2 or by the observed measure of inequality $\frac{W_j^{80}}{W_j^{20}}$.

Holding compensation and inequality measures constant, job satisfaction, promotion satisfaction and social status are all increasing with age. Job satisfaction and social status are increasing with years of education. Holding the four objective measures constant, older, female, rural and educated workers experience higher level of job satisfaction and social status. Older, female and rural workers perceive higher promotion satisfaction. Those who work in the government departments have the highest level of job satisfaction, promotion satisfaction and social status, while those who work in private sector firms have lower levels of all three measures.

We can compare this result with the past literature. Simon Luechinger, Stephan Meier and Alois Stutzer (2010) studied the case in Germany, United States and Europe to conclude that employees working in public sectors have higher level of job security against unemployment and reacts less sensitively to fluctuations in unemployment rates. Jose Maria Millan, Jolanda Hessels, Roy Thurik and Rafael Aguado (2013) compared the levels of job satisfaction between self-employed and paid-employed workers in Europe. They found that self-employed workers are more likely to be satisfied with their jobs in terms of type of work, but less satisfied in terms of job security. Kwangho M. Jung, Jae Moon and Sung Deuk Hahm (2007) studied the job satisfaction case in Korea, which has a cultural background similar to China. They found public and non-profit employees are more satisfied with their jobs than private employees, but less satisfied with their wages than with their job security and job content. Our result is consistent to the findings in the literature.

Conclusion

In this paper, we aimed at analyzing the distribution of Chinese worker's perceptions concerning job satisfaction, promotion satisfaction as well as social status, and how they're affected by the objective measures of treatment, inequality and relative income. The most important finding of our paper is that relative income positively affects job satisfaction, promotion satisfaction and social status. The effects of income inequality is complicated and differ by its observability. Also, we found that worker's perceptions of job satisfaction, promotion satisfaction and social status in China are not much affected by objective information concerning treatment, inequality or relative income. This result is quite consistent to the previous literature on job satisfaction, no matter in the case of the US, UK, Germany or China. We can explain this by inferring that information release is not complete in the labor market or most of workers do not care about such information concerning their wages, income inequality or relative status, no matter in developed countries or in developing countries, and worker's perceptions of job satisfaction or social status are more dependent on their personal experiences. At the same time, the fact that the objective measures of income inequality, no matter unobservable or observable measures, do not have statistically significant influence on worker's job satisfaction, promotion satisfaction or social status implies that Chinese workers do not seem to perceive the actual inequality or care about it, and the objective information of inequality does not affect job satisfaction, promotion satisfaction or social status significantly. This is quite consistent to recent studies on the deviation between the actual inequality and perceived inequality, like Vladimir Gimpelson and Daniel Treisman (2018). However, we only investigated the effects of the objective measures of inequality, but are still unaware of the perceived inequality's effects. That is what need to be further studied in the future.

We found that employees working in the government departments have the highest level of job satisfaction, promotion satisfaction and social status. By comparing with the past literature we can see our results are consistent to the findings in the literature concerning job satisfaction in different types of employers, and we can infer in our study, the workers in government departments have higher level of job satisfaction probably because they job is less risky than in other types of employers; the self-employed workers also have higher level of job satisfaction and social status than their paid-employed counterparts probably because they value the type of work over job security.

At the same time, we found in our result that while holding other things constant, job satisfaction, promotion satisfaction and social status are all increasing with age, and longer years of education brings higher level of job satisfaction and higher social status. By comparing with the results in Table 2, Table 3 and Table 4, we can infer that since income increases with age until the worker nearly retire as analyzed from Table 3, and the old workers get paid more than they desire, as is shown in Table 4, it's reasonable that job satisfaction and social status increase with age. Similarly, Table 3 reveals that income increases with years of education, and Table 4 shows that educated workers get paid much higher above the average, so they have higher level of job satisfaction and higher level of social status as compared to their uneducated counterparts when holding other things constant. This should be a possible explanation.

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Figures and Tables

Table 1 Summary of the critical questions and valid answers

Number	Question	Valid Answers
1	In general, how satisfied are you with this job? (Corresponding variables: Job Satisfaction)	The valid answers can be "Very unsatisfied", "Somewhat unsatisfied", "Fair", "Somewhat satisfied", "Very satisfied". They can be represented by numbers 1-5 respectively.
2	How satisfied are you about the promotion opportunity of this job? (Corresponding variable: Promotion Satisfaction)	The valid answers can be "Very unsatisfied", "Somewhat unsatisfied", "Normal", "Somewhat satisfied", "Very satisfied". They can be represented by numbers 1-5 respectively.
3	What is your social status in your local area? (Corresponding variable: Social Status)	*Social status* is measured from 1-5 "1" means "Very low" "5" means "Very high"

Source: CFPS database, 2014 cross-sectional dat

Table 2 A summary of worker's perceptions of job satisfaction, promotion satisfaction, social status and t-statistics of test of difference in means

Related Question	Question 1		Question 2		Question 3	
Response	Job Satisfaction		Promotion Satisfaction		Social Status	
Demographic Group	A	B	A	B	A	B
Old(A) vs Young(B) [a]	3.66 [b]	3.37	3.00	3.00	2.95	2.75
t-statistics	8.53 [c]		0.04		6.08	
Male(A) vs Female(B)	3.44	3.45	3.01	3.00	2.85	2.89
t-statistics	0.55		0.68		3.22	
Urban(A) vs Rural(B)	3.43	3.46	3.00	3.02	2.76	2.97
t-statistics	2.27		0.96		16.47	
Educated(A) vs Uneducated(B) [d]	3.60	3.52	2.98	3.04	2.92	2.99
t-statistics	2.52		1.40		2.33	
Han(A) vs Minority(B)	3.39	3.24	3.03	2.99	2.72	3.05
t-statistics	2.12		0.50		4.81	
Overall Average	3.45		3.01		2.87	

Source: CFPS database, 2014 cross-sectional data

[a] Old: Age≥60; Young: Age<35

[b] The values in this table are all average values of the ratings by corresponding demographic groups.

[c] Here we report the t-statistics of the tests of difference in means between different demographic groups

[d] Educated: Schooling≥ Bachelor's Degree; Uneducated: Schooling≤ Primary School

Table 3 Results of Regression of Model (1)

Number of obs=8,600 F(31,8568)=69.990 Prob>F=0.000 R^2=0.202 Adjusted R^2=0.199		
Variables	Coefficient	t-statistics
ln(Wage) (dependent variable)		
Schooling	0.184	(28.09)
Experience	0.157	(30.17)
Experience^2	-0.002	(27.08)
Schooling*Experience	-0.004	(17.93)
Region (Reference: Shanghai)		
Yunnan-Shanghai[a]	-0.601	(7.02)
Inner Mongolia-Shanghai	-0.669	(1.41)
Beijing-Shanghai	-0.138	(1.08)
Jilin-Shanghai	-0.797	(8.28)
Sichuan-Shanghai	-0.578	(8.04)
Tianjin-Shanghai	-0.244	(1.81)
Anhui-Shanghai	-0.439	(4.81)
Shandong-Shanghai	-0.459	(6.42)
Shanxi-Shanghai	-0.646	(8.89)
Guangdong-Shanghai	-0.286	(5.09)
Guangxi-Shanghai	-0.883	(9.49)
Xinjiang-Shanghai	-0.292	(0.39)
Jiangsu-Shanghai	-0.270	(3.51)
Jiangxi-Shanghai	-0.451	(5.22)
Hebei-Shanghai	-0.626	(9.87)
Henan-Shanghai	-0.536	(10.03)
Zhejiang-Shanghai	-0.187	(2.27)

[a] Yunnan-Shanghai means when the value of the provincial dummy variable "Province" changes from "Shanghai" to "Yunnan". All of the following ones are the same.

Table 3 Continued

Hainan-Shanghai	-0.822	(1.10)
Hubei-Shanghai	-0.733	(7.58)
Hunan-Shanghai	-0.433	(5.39)
Gansu-Shanghai	-0.572	(10.51)
Fujian-Shanghai	-0.569	(4.96)
Guizhou-Shanghai	-0.723	(8.77)
Liaoning-Shanghai	-0.442	(7.67)
Chongqing-Shanghai	-0.497	(3.23)
Shaanxi-Shanghai	-0.555	(6.15)
Heilongjiang-Shanghai	-0.598	(7.80)
Constant	7.263	(71.73)

Source: CFPS database, 2014 cross-sectional data

Table 4 A summary of objective measures of treatment, inequality, relative income and t-statistics of test of difference in means

	Individual Measures				Market Measures			
	ε_{ij} [a]		$\frac{W_{ij}}{\overline{W_j}}$		(σ_j^2) [b]		$\frac{W_j^{80}}{W_j^{20}}$	
Demographic Groups	A	B	A	B	A	B	A	B
Old(A) vs Young(B)	0.56 [c]	0.07	0.72	0.99	1.15	1.14	4.19	4.22
t-statistics	5.53		5.46		1.63		1.19	
Male(A) vs Female(B)	0.17	-0.26	1.14	0.78	1.13	1.13	4.23	4.23
t-statistics	18.86		24.07		0.75		0.15	
Urban(A) vs Rural(B)	-0.01	0.01	1.05	0.95	1.10	1.16	4.04	4.37
t-statistics	0.72		6.84		15.30		30.95	
Educated(A) vs Uneducated(B)	-0.07	0.02	1.38	0.78	1.05	1.13	4.01	4.37
t-statistics	1.89		12.34		11.48		12.96	

[a] The deviation of actual log wage from the fitted value of log wage, which represents the objective measure of the part that an individual is overpaid or underpaid unexplained by Mincer Earnings function.

[b] The variance of ε_{ij} by province, which marks the objective measure of provincial income discrimination unexplained by Mincer Earnings function. This measure is unobservable in the labor market.

[c] The numerical values in the table are average values across provinces of the corresponding demographic group, but note that the values of $\overline{W_j}$ are the average values across provinces of the total sample, not of the corresponding demographic group.

Table 4 Continued

Han(A) vs Minority(B)	-0.63	1.31	1.09	1.22	1.13	1.28	4.07	5.13
t-statistics	4.57		1.40		8.20		15.69	
Overall Average Value	-2.77×10^{-9}		1.00		1.13		4.23	

Source: CFPS database, 2014 cross-sectional data

Table 5 Results of Regression of Model (2)

Perceptions (Elasticities reported)	Job Satisfaction		Promotion Satisfaction		Social Status	
	A	B	A	B	A	B
Unexplained Wage: ε_{ij}	-0.001[a] (0.25)[b]	0.019 (3.52)	0.015 (2.06)	0.020 (2.39)	-0.010 (2.54)	0.002 (0.42)
Provincial Wage Error Variance: σ_j^2	-0.053 (0.55)	0.017 (0.17)	-0.097 (0.74)	-0.116 (0.88)	0.059 (0.47)	0.059 (0.45)
Wage Relative to Provincial Mean: $\frac{W_{ij}}{\overline{\overline{W}}_j}$	0.281 (6.84)	0.167 (3.76)	0.151 (2.83)	0.163 (2.82)	0.437 (8.05)	0.361 (6.07)
Provincial Percentile Wage Gap: $\frac{W_j^{80}}{W_j^{20}}$	-0.071 (0.56)	-0.111 (0.85)	-0.106 (0.62)	-0.159 (0.92)	-0.180 (1.05)	-0.309 (1.75)
Age	-	0.735 (7.83)	-	0.234 (1.93)	-	1.130 (8.93)
Male	-	-0.103 (3.20)	-	-0.073 (1.76)	-	-0.136 (3.21)
Urban	-	-0.091 (2.87)	-	-0.075 (1.76)	-	-0.343 (7.71)
Education	-	0.319 (4.07)	-	-0.099 (0.94)	-	0.232 (2.23)
Government-State owned enterprise[c]	-	-0.078 (6.59)	-	-0.049 (3.06)	-	-0.088 (5.76)
Government-Private sector firm	-	-0.408 (8.73)	-	-0.175 (2.78)	-	-0.488 (8.22)

[a] For all of the perceptions of Job Satisfaction, Promotion Satisfaction and Social Status, Ordered Probit model is adopted, the numbers reported in the cells are the elasticities.

[b] The numbers reported in the parentheses are the z-statistics of the corresponding regressions.

[c] Government-State owned enterprise means holding the other factors constant, the perceptions of one who works in a state –owned enterprise compared to that in the government departments. And so are the interpretation of Government-private sector firm and Government-Individuals. Here we hold the government departments as the reference employer.

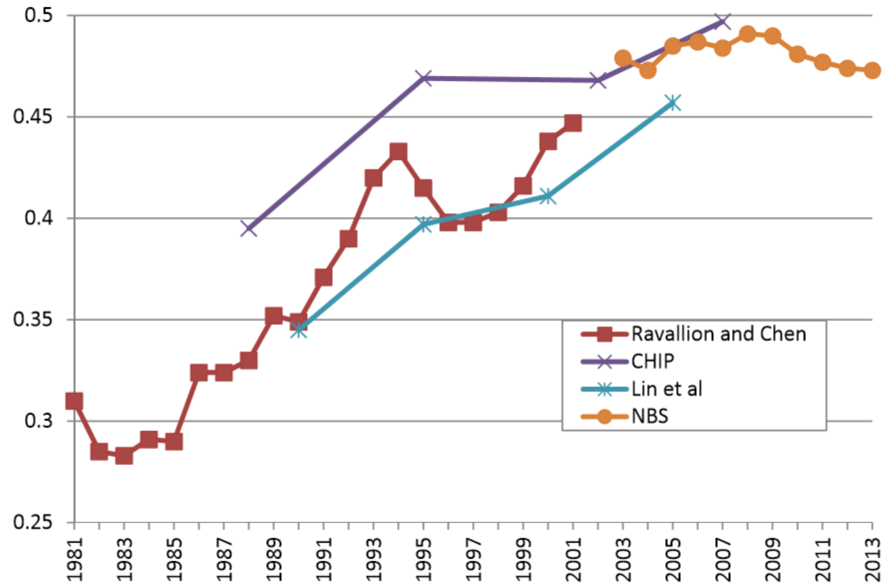
Table 5 Continued

Government-Individuals	-	-0.058 (6.45)	-	-		-0.040 (3.34)
Unobserved measures: $\chi^2(2)$ test [a] $\varepsilon_{ij}, \sigma_j^2=0$	12.51		6.43		0.38	
Pseudo R^2 [b]	0.0009		0.0004		0.0000	
Observed measures: $\chi^2(2)$ test $\frac{W_{ij}}{\overline{W_j}}, \frac{W_j^{80}}{W_j^{20}}=0$	14.83		8.62		39.48	
Pseudo R^2	0.0010		0.0006		0.0027	
Individual measures: $\chi^2(2)$ test $\varepsilon_{ij}, \frac{W_{ij}}{\overline{W_j}}=0$	85.70		43.58		77.91	
Pseudo R^2	0.0057		0.0033		0.0054	
Market objective measures: $\chi^2(2)$ test $\sigma^2, \frac{W_j^{80}}{W_j^{20}}=0$	0.75		2.73		3.15	
Pseudo R^2	0.0001		0.0002		0.0002	
Demographics: $\chi^2(7)$ test Age, Male, Urban, Education, Government-State owned enterprise, Government-Private sector firm=0	203.30		24.22		238.03	
Pseudo R^2 of model A and B	0.0055	0.0190	0.0028	0.0046	0.0057	0.0221
Model of Estimation	Ordered Probit	Ordered Probit	Ordered Probit	Ordered Probit	Ordered Probit	Ordered Probit

Source: CFPS database, 2014 cross-sectional data. Critical value of the $\chi^2(2)$ test at the 0.05 confidence level is 5.99. *Critical value of the* $\chi^2(7)$ test at the 0.05 confidence level is 14.07.

[a] The tests are aimed at examining if the group of measures are jointly significant in the complete model

[b] The pseudo R^2 here means the pseudo R^2 from the regression of only the corresponding group of measures, in order to compare the contribution of the groups of measures make to the explanation power of the model.



Note: Figure 1 reveals Gini Coefficients Based on Household Survey Data. CHIP=Chinese Household Income Project; NBS=National Bureau of Statistics. Gini coefficients from Ravallion and Chen (2007) and Lin et al. (2010) are based on nonadjusted data.

Source: Wang, Chen, Guanghua Wan, and Dan Yang. "Income inequality in the People's Republic of China: trends, determinants, and proposed remedies." *Journal of Economic Surveys* 28.4 (2014): 686-708.

Figure 1 China's Gini Coefficients summarized from various sources

CHAPTER 3. A STUDY ON CHINESE CONSUMER'S MEAT CONSUMPTION PATTERNS AND THEIR TRANSITIONS

Abstract

We use the 2006, 2009, 2011, and 2015 Urban Household Survey data to study Chinese consumers' meat consumption patterns for each year of the survey and investigate how they change over time and across provinces, as well as across income groups. We apply a censored demand system approach with an Almost Ideal Demand System specification and report statistics of meat consumption, average household income, income elasticities, Marshallian price elasticities, and Hicksian price elasticities to reveal meat consumption patterns among Chinese consumers.

We find that as average household income increases, meat expenditures have increased, with pork capturing a slightly larger share, because the rapid increase in beef, mutton and chicken prices reduce their expenditure shares. And while the data are refined enough to find statistically significant differences across the provinces and across income groups, the general pattern for elasticities holds across both provinces and income groups. Pork and other meats are viewed as necessities, while beef, mutton, and chicken tend to be luxury goods. The meat consumption changes imply a great opportunity for U.S. pork export growth if China exempts retaliatory duties on U.S. pork exports.

Key Words: Meat consumption patterns, censored demand system, African swine fever, elasticities, U.S. pork exports

Introduction

China has experienced fast economic growth in the last few decades—in recent years it has become the second-largest economy in the world. Food consumption patterns of Chinese consumers have changed a lot over years due to rapid income growth. Wang, Jensen, and Johnson (1993) conclude that Chinese consumers' food consumption patterns shifted from grains to meat and other high-value food products, such as eggs. They summarized that total animal protein in the Chinese diet increased from 8.37% in 1979 to 20.53% in 1991. As Chen et al. (2015) show, the growth of average household income has changed Chinese consumers' meat consumption patterns. Due to China's population size and large economy, even small changes in the average consumer's meat consumption patterns lead to large increases in meat demand due to aggregation, which further impacts meat production and trade. As China increasingly participates in the world market, changes in Chinese consumers' meat consumption patterns have a significant impact on the rest of the world's animal product and farming industries.

Figure 1 and Table 1 show trends in China's production of pork, beef, chicken, and a total of all three meats from 2000 to 2016. In general, from 2000 to 2016 the production of pork, beef, and chicken increased. Pork production levels were much higher than that of beef and chicken. While beef and chicken production are relatively flat over the years, the production curve for pork kept increasing, but did suffer setbacks in 2007 and 2011.

These pork production setbacks were the result of severe outbreaks of swine diseases in China in 2007 and 2011. In 2007, a highly infectious virus, blue-ear pig disease, (McOrist, Khampee, and Guo 2011) spread to most provinces in China and 50 million of pigs were affected, which lead to a pork shortage and rising pork prices. Figure 2, drawn using the data from China Yearbook of Agricultural Price Survey 2004-2016, shows that the rural market pork prices in

China began rising in 2007 and peaked in 2008, which is consistent with the 2007 outbreak of blue-ear pig disease.

In 2011, China saw an outbreak of porcine epidemic diarrhea virus (PEDv). PEDv was sporadic before 2010, but quickly spread to many of China's pig-producing provinces near the end of 2010. In 2011, the disease spread throughout China, causing huge economic losses, creating a pork shortage, and driving pork prices up (see table 2 and Figure 2).

Figure 3 shows the strong relationship between pork production and consumption in China. Reviewing historical outbreaks of swine diseases in China may provide a better understanding of consumers' meat consumption pattern changes, as historical information may reveal some potential factors that contribute to changes in meat consumption patterns. It may also shed some light on the effects of similar events that have taken place in recent years, and provide a better understanding of the losses or opportunities these events might bring.

In 2019, China saw a severe outbreak of African Swine Fever (ASF). ASF has had a serious impact in Asia, causing large-scale pig losses in Vietnam, Laos, South Korea, Cambodia, and especially China. China's domestic pork prices skyrocketed due to the huge losses in production; whereas ASF brought great opportunities for growth to the U.S. pork export industry. However, the United States and China entered a trade war in 2018, and the duties China imposed on U.S. pork exports counteracted chances of growth for U.S. exports. Through continuous efforts from both parties, the U.S. and China reached a trade deal in the first phase of the trade war. The United States would reduce the new tariff rates imposed on $120 billion Chinese products to 7.5%, and China agreed to purchase $200 billion products and services from the United States in the following two years-including $50 billion agricultural products, like pork, beef, poultry, seafood or soybean. The increase in China's import of U.S. pork would reignite the opportunity for U.S.

pork export growth. Hence, investigating changes in Chinese consumers' meat consumption patterns in recent years might shed some light on policy changes, and help estimate the influence of the trade war; thus, it has great significance both in academic research and in the real world economy.

A review of the literature shows many studies have examined Chinese consumers' meat consumption patterns. Lewis and Andrews (1989) use an extended linear expenditure system to estimate the food demand of rural and urban households in China. They investigate demand for broad groups of commodities and specific types of meat like pork, poultry, and fish. They find pork is about unit elastic, while poultry and fish are luxuries. In general, they conclude that basic needs take a large proportion of the average Chinese household's income. Gao, Wailes, and Cramer (1996) investigate economic and demographic influences on China's rural household's food demand (including major types of meat, like pork, beef, lamb and poultry) in Jiangsu province; and, using a two-stage budgeting approach, they find that income stagnation caused the slow growth of food consumption in Jiangsu in the late-1980s. They also discover that Chinese peasants' willingness to build a house had a squeeze effect on rural household food consumption. Ortega, Wang, and Eales (2009) study meat demand in China by estimating a linear Almost Ideal Demand System (AIDS) model. Using time series data from 1980 to 2003, they find that pork—the primary meat in Chinese consumers' diets—has become a necessity, while poultry, beef, mutton, and fish are still taken as luxuries within the meat budget allocation of Chinese households. Liu et al. (2009) analyze China's urban and rural meat consumption, respectively, using cross-sectional data from their own 2005 household survey. They find that income and prices are the two major factors that influence Chinese consumers' at-home meat consumption patterns—affecting, not only meat consumption levels, but also the composition of meat consumption.

Specifically, they find that as income increases, pork remains dominant in meat consumption. Meanwhile, consumers diversify their meat expenditures and will seek out higher quality and safer meats. When compared to away-from-home meat consumption, Chinese consumers are more responsive to meat prices when they consume them at home.

Many factors, such as prices, income, demographic effects, and consumers' preferences affect meat consumption. While plenty of studies investigate the influences of prices, income, and demographics, several studies also investigate preferences. Sakong and Hayes (1993) develop a framework of linear programming that solves for income elasticities and changes in food tastes. Wan (1998) uses this framework with additional constraints to identify taste changes in the demand for seven food items, including meat in 28 rural regions in China, and finds Chinese consumers' preferences move towards meat and other commodities, including wheat, alcohol, and coarse grain, driven by income growth.

The aforementioned studies reveal Chinese consumers' meat consumption patterns, as well as their changes, from different perspectives. They provide useful information about changes in demand in the world's meat market, and provide guidance for further development of the world's meat industry. However, the data used in these studies are relatively old and do not provide information about meat consumption patterns in recent years. Updated information on meat consumption provides useful information for effective industry planning, market access negotiations, and successful marketing programs within and outside of China (Liu et al. 2009).

What was China's meat consumption like in the most recent decade? Did China's rapid economic growth bring any new changes to consumers' meat consumption patterns? What policy implications does China's meat consumption patterns reveal? In the most recent decade, there has been very little research in this field, and these are questions that need answers.

We investigate meat consumption in China using recent data, and compare the results to those from previous studies to reveal patterns. Specifically, I use the 2006, 2009, 2011, and 2015 cross-sectional data collected from the Urban Household Survey (UHS) database to explore meat consumption patterns and their changes over the years in four typical urban provinces in China—Liaoning, Shanghai, Guangdong, and Sichuan—while controlling for the demographic characteristics of households. We study the meat consumption pattern and its transition in the four provinces as a whole, as well as the pattern in each province, respectively. We also examine potential differences among income groups within Liaoning province to account for possible heterogeneity.

Literature Review

Previous studies examine the background of the U.S.-China trade war and the outbreak of ASF and estimate the corresponding effects that they bring to the economy. Zhang, Hayes, and Li (2018) estimate China's import potential if China removes tariff and non-tariff barriers. They investigate the major commodities that China imports from the United States and find that China's pork imports from the United States could potentially increase by $8.9 billion if trade barriers are removed. Carriquiry et al. (2019) establish two scenarios to study damages caused by the retaliatory duties that China imposed on U.S. pork and soybean exports using the CARD-FAPRI modeling system to study the first and second round of impacts brought about by the ASF outbreaks. They find that a persistent 30% decline in Asian hog inventory could potentially bring over $7 billion in growth to the U.S. pork export industry. They also find the gap in China's pork market brought about by ASF could drive U.S. pork prices up from $50/cwt to nearly $60/cwt.

To estimate how Chinese consumers change their meat consumption patterns, we need to use demand system models to estimate the relevant demand elasticities of meats. Most studies, generally speaking, estimate meat and food consumption patterns in China by estimating a proper demand system model and using the estimated parameters to calculate price elasticities and, if possible, income elasticities for each kind of meat. Wu, Li, and Samuel (1995) examine urban household consumption patterns in China using aggregated household consumption data. Using estimated demand elasticities, they find that pork has relatively low own-price elasticity, which reflects that it is more essential in Chinese household's consumption patterns. They also find the relatively high income elasticity of pork is consistent with other relevant studies, suggesting the potential for a large Chinese market for non-staple foods. Fan, Wailes, and Cramer (1995) use a two-stage LES-AIDS model to study the consumption patterns of Chinese rural households. They used the Linear Expenditure System (LES) for the first stage of regression and adopted Almost Ideal Demand System (AIDS) for the second stage, and find that meat has relatively higher expenditure elasticity among food groups. Dong and Fuller (2010) use both parametric and nonparametric methods to test the structural change in Chinese urban citizens' diets. They find that meat, vegetables, fruits, and fish are frequently identified in the tests, showing evidence of structural change. They also find that the greatest changes occur in consumers' responses to price changes, and consumers' demands become less price elastic.

These studies provide useful information about Chinese consumers' meat demand patterns by estimating demand system models and reporting demand elasticities. However, they are ineffective because they do not take into account the zero expenditure records that usually exist in meat consumption databases. Most studies use econometric models that assume expenditures (or shares) follow a joint normal distribution that does not allow for a positive probability of zero expenditure. Excluding zero expenditure records in the data leads to biased and inconsistent estimation of parameters and reduces the sample size (Wales and Woodland 1983). Thus, economists developed a censored demand system approach to correct the bias. Yen and Huang (2002) use a censored translog demand system to estimate demands for beef products using data from the U.S. Department of Agriculture 1987–88 Nationwide Food Consumption Survey. Salvanes and DeVoretz (1997) use Heien and Wesseills' (1990) two-step procedure to estimate Canadian demand for disaggregated fish and meat products and substitute the missing price values of zero consumption with the predicted prices from the demographic characteristics. Since these studies do not impose the budget constraint on the observed shares, the results might be biased. Yen, Fang, and Su (2004) use a censored demand system approach to study urban household food consumption in China. They find that most meat products have high expenditure elasticities, and that demographics have some impacts on food demand. Dong, Gould, and Kaiser (2004), Dong, Kaiser, and Myrland (2007), and Dong, Davis, and Stewart (2015) use the censored AIDS model and Amemiya-Tobin approach with budget constraints imposed on both the observed and latent systems to correct the bias and estimate disaggregated meat consumption in Mexico, Norway, and the United States, respectively. In this study, I adopt the approach of Dong, Davis, and Stewart (2015) to estimate disaggregated meat consumption in China.

Typically, researchers use one of two different censored demand system approaches—the Kuhn-Tucker approach and the Amemiya-Tobin approach. Wales and Woodland (1983) formulate both censored demand system approaches. The Kuhn-Tucker approach is based on Kuhn and Tucker's (1951) conditions for utility maximization subject to a budget constraint. The Amemiya-Tobin approach is based on a limited dependent variable model by Tobin (1958) for the case of a single equation, and by Amemiya (1974) for a set of equations. Compared to the Kuhn-Tucker approach, the Amemiya-Tobin approach is easier to implement and avoids the incoherency problem by mapping the latent shares to observed expenditure shares. Dong, Gould, and Kaiser (2004), Dong, Kaiser, and Myrland (2007) and Dong, Davis, and Stewart (2015) extend the Amemiya-Tobin approach using an AIDS specification, and impose the budget constraints to both the observed and latent systems. Given the improvements and the advantages of their method, I adopt Dong, Davis, and Stewart's (2015) extended Amemiya-Tobin approach for estimation.

Methodology

Model Estimation

We choose four specific types of meat for estimation—pork, beef, mutton, and chicken—and then aggregate all other types of red meat and poultry into "other meats." Thus, I estimate demand for five types of meat in total. If we assume at least one kind of meat is consumed for each individual, then there is 2^5-1=31 different regimes of consumption. Except for the regime in which all five meats are eaten, there will always be one or more kinds of meat not consumed during the survey period. I record those expenditures as zeros; and, as mentioned, zero expenditure records lead to biased and inconsistent estimation. Thus, we use Dong's extended Amemiya-Tobin approach (2015) to estimate my model in order to avoid bias issues.

We assume that there are N individual consumers, and each consumer can eat up to M+1 different kinds of meat. Thus, we can derive the M+1 latent share (W^*) equations from utility maximization, which I express as:

$$W^* = U + \varepsilon \tag{1}$$

where U is the non-stochastic part of the latent share W^*; and, ε is a (M+1)×1 random error term vector. Using Deaton and Muellbauer's (1980) AIDS model, we have $U = \alpha + \beta X + \gamma \ln P + \eta \ln Y$

, where P is a (M+1)×1 column vector of meat prices, and α is a constant term; and X is an [L×1] vector of individual demographic characteristics. Here, $Y = \frac{y^*}{P^*}$, where y* is the total expenditure of a typical consumer and P* is a translog price index, which is defined by:

$$\ln P^* = \alpha_0 + \alpha' \ln P + \frac{1}{2}(\ln P)' \gamma (\ln P) \tag{2}$$

where the parameters are $\alpha[(M+1)\times 1]$; $\beta[(M+1)\times L]$; $\gamma[(M+1)\times(M+1)]$; $\eta[(M+1)\times 1]$; and, $\alpha_0[1\times 1]$. The budget constraints are $I_{(M+1)}U = 1$ and $I_{(M+1)}\varepsilon = 0$, where I is a 1×(M+1) unit vector. The budget constraint $I_{(M+1)}U = 1$ is obtained by imposing the parameter restrictions $I_{(M+1)}\alpha = 1$, $I_{(M+1)}\beta = 0$, $I_{(M+1)}\gamma = 0$, and $I_{(M+1)}\eta = 0$. Also, constraints like homogeneity and symmetry are assumed on equation (1). The symmetry constraint is $\gamma = \gamma'$; and, given the symmetry and budget constraints, the homogeneity requirement is automatically met.

From the constraint $I_{(M+1)}\varepsilon = 0$, we know that the joint density function ε is singular; thus, when we estimate the model, we drop one of the M+1 latent share equations. Afterwards, we can use the budget and symmetry constraints to retrieve the parameters of the dropped latent share equation through the other estimated parameters. We assume that the last one of the M+1 latent share equations is dropped, and the remaining M share equations' error terms, ε, follow a multivariate normal distribution; that is, $\varepsilon \sim MN(0, \Sigma)$, where Σ is an M×M error covariance matrix.

When using the Amemiya-Tobin approach, we also need to map the latent share (W*) to the observed share (W). Wales and Woodland's (1983) mapping formula is as follows:

$$W_i = \begin{cases} \dfrac{W_i^*}{\sum_{j\in\Psi} W_j^*}, & if \quad W_i^* > 0 \\ 0, & if \quad W_i^* \le 0 \end{cases} \qquad \text{(i= 1, 2, …, M+1)} \tag{3}$$

where Ψ is the set of all the positive latent shares, i represents the ith meat share and j represents the jth positive latent share. Using this mapping guarantees that the observed share W_i lies between 0 and 1, and sums to 1 for each individual.

We use the maximum likelihood estimation method to estimate the parameters in our model. As this estimation approach requires calculating a very complicated likelihood function and derivatives, and it is impractical to do it directly, the best approach is the GHK smooth recursive probability simulation procedure proposed by Geweke (1991), Hajivassiliou, McFadden, and Ruud (1996), and Keane (1994).

As Dong, Gould, and Kaiser (2004) show, after obtaining the parameters estimation, it is feasible to calculate the corresponding income and Marshallian price elasticities of each kind of meat. We use simulation to achieve this calculation, as it is very complicated and impractical to do the calculations directly. Assume we generate T replicates of the (M+1)×1 error term vector ε , and calculate the sample means of the exogenous variables (with a bar symbol over the variable), then the k*th* simulated latent share W_k^* is expressed as:

$$W_k^* = A + \gamma \ln \overline{P} + \eta \ln \frac{\overline{y}}{P^*} + \varepsilon_k \tag{4}$$

where ε_k is the k*th* replicate of ε. Then, we can write the k*th* replicate of the i*th* observed share as:

$$W_{ik} = \begin{cases} \dfrac{W_{ik}^*}{\sum_{j \in \Psi} W_{jk}^*}, & if \quad W_{ik}^* > 0 \\ 0, & if \quad W_{ik}^* \le 0 \end{cases} \tag{5}$$

Here j represents the jth positive simulated latent share. The expected observed share vector can be obtained by taking the average of the K replicates of the simulated values:

$$E(W) = \frac{1}{K}\sum_{k=1}^{K} W_k \tag{6}$$

Elasticities Estimation

In order to estimate the elasticities of the AIDS model, including income elasticities and Marshallian price elasticities, we followed both a conventional and a simulation approach using the following formulas. We estimated the elasticities following the conventional method from Green and Alston (1990), deriving the elasticities directly from the AIDS model parameter estimates. We also checked those against simulations from the model constructed in the following manner.

We suppose a very small price change ΔP_j takes place in price j, then we can obtain the corresponding Marshallian price elasticities vector of a certain type of meat as follows:

$$\eta_j = -\delta_j + \frac{\Delta E(W_j)}{\Delta P_j} \cdot \frac{P_j + \Delta P_j / 2}{E(W_j) + \Delta E(W_j)/2} \tag{7}$$

where δ_j is a vector of 0's only when the *jth* argument equals one; and, $\Delta E(W)$ is the change in the simulated expected share caused by the change in price ΔP_j. We can name $P_0 = P$ as the original price of meat, and the new price of meat will be $P_1 = P + \Delta P_j$. With the parameters estimated in the AIDS model, we substitute P_0 and P_1 to equations (4) respectively to get the original latent share W^* and the new latent share W_1^*, and use equation (5) to map the latent shares to the simulated observed shares W and W_1. Then we use equation (6) to get the average simulated observed shares, E(W) and $E(W_1)$, and calculate the difference to get $\Delta E(W) = E(W_1) - E(W)$. Then, we substitue $\Delta E(W)$ and E(W) as well as P and ΔP_j to equation (7) to get the Marshallian price elasticities of each kind of meat.

We use the two-stage budgeting approach to calculate the income elasticity of each meat because there are too many variables relative to the number of observations available for estimation. In the first stage, we categorize all of the commodities consumed into broad groups—staple foods, vegetables and fruits, meats, seafoods, eggs and milk, drinks, and other goods. We estimate the AIDS model using the same format as described in equations (1) and (2); however, in this instance y^* on the right-hand side represents household income instead of expenditure. Then, similar to what we did above for estimating the Marshallian price elasticities of each kind of meat, we calculate the income elasticities of each broad commodity group as follows (here y^* represents household income and what makes a small change here is household income):

$$\eta_j = \frac{\Delta E(W_j)}{\Delta y^*} \cdot \frac{P_j + \Delta y^* / 2}{E(W_j) + \Delta E(W_j)/2} \tag{8}$$

Here Δy^* is the change in average household income. We are able to calculate the income elasticity of meats—an aggregation of pork, beef, mutton, chicken, and other meats—by estimating the income elasticities of each broad commodity group.

In the second stage, we estimate the expenditure elasticity of each meat within the broad group of "meats." Similar to the first stage, we first estimate the AIDS model, as in formulas (1) and (2); however, here y* represents total expenditure on meats. I then estimate the expenditure elasticity of each meat within the "meats" group using equation (8), where y* represents total expenditure on meats instead of household income. The income elasticity of meat is then the product of expenditure elasticity of each meat within the broad group of "meats," multiplying the income elasticity of the broad group "meats."

The comparison between the elasticities calculated using our formulas (7) and (8) and the elasticities calculated based on parameters elstimated using conventional approaches provided in

Green and Alston (1990) shows that our formulas (7) and (8) are equivalent to the conventional approach. The results of our comparison indicate that the results calculated using the two different approaches are within rounding errors.

Data

We select cross-sectional data from the 2006, 2009, 2011, and 2015 UHS database for our estimation. Due to a data availability constraint, we only have access to UHS data from the provinces of Liaoning, Shanghai, Guangdong, and Sichuan. From our analysis in Table 5A and Table 6A-6E, we can see that in general, provincial heterogeneity doesn't play a big role in Chinese consumer's meat consumption pattern because each province mostly follow the same consumption pattern of the country as a whole. Thus, we can assume these four sample locations are typical and can represent the whole nation, not only because they're similar to the whole nation in their meat consumption behaviors but also geographically, they are located in north, east, south, and southwest China, respectively, and they are similar in their traditions to the other provinces in the same region.

Table 2A-2E and Table 3 show Chinese urban household's average daily consumption levels of each type of meat in the four selected provinces. We report the overall consumption of the four provinces to represent the whole nation, and also report the consumption in each province as well as the consumption among low, middle and high income groups in Liaoning province to reveal heterogeneity of consumption in different regions or in different income levels. Table 4A and 4B display Chinese urban household's average monthly income in the four selected provinces as a whole, and in each province respectively as well as in different income groups within Liaoning. For comparison, we also report Chinese urban household's average national meat consumption levels and average national monthly income calculated from China Statistical Year Book, as shown in tables 2A-2E and 4A, respectively. The China Statistical Year Book only shows consumption levels for poultry (not just chicken); however, as tables 2A-2E and 4A show, average household meat consumption and average monthly household income in the four sample provinces are similar to those at the national levels. Thus, we consider the four sample provinces—Liaoning, Shanghai, Guangdong, and Sichuan—representative of China's urban areas.

UHS datasets contain information on household food consumption amounts, household food expenditures, household income, and some demographic characteristics. We calculate average prices of each meat by dividing the corresponding meat expenditure over the amount of meat consumed. These household level meat prices can be used for regressions. Table 2A shows that in 2015 consumption of pork increased when there was a slight decrease in pork price, and Tables 2B-2E show that beef, mutton, chicken, and other meat consumption were stable. Pork prices increased from 2006 to 2011, but slightly decreased from 2011 to 2015. During that same time, beef and mutton prices skyrocketed and chicken and other meat prices were relatively stable. By comparing the meat expenditure shares across all four sample years, we find that pork is always the most popular meat among Chinese consumers and accounts for about a half of household's total meat expenditure. From 2006 to 2015, mutton expenditure shares were stable, but shares of beef, chicken, and other meats declined, and the share of pork went up. This shows that recently Chinese urban consumers have shifted their preference from beef, chicken, and other meats to pork. Figure 2 gives the price trend of pork in China's rural market affairs for reference. Table 2A-2E show that while pork was always the mostly consumed type of meat among urban Chinese households, beef, mutton, and chicken account for a small portion in total expenditure shares, and other meats account for a fair portion. Mutton has always been the least-consumed meat.

Exploring the differences across provinces, we can see from Table 2A-2E that Guangdong consumes the largest amount of pork and chicken, and Sichuan is the second largest consumer of pork. Shanghai and Liaoning pork consumption levels are relatively low, but Shanghai is a little bit higher in chicken consumption. Mutton consumption in Liaoning is lower than that in the other three provinces, and mutton prices in Shanghai and Guangdong are relatively higher. For other meats consumption, Guangdong takes the lead in consumption amount, while Guangdong and Shanghai have relatively higher prices than the other two provinces.For the different income groups within Liaoning, we can see in Table 3 that pork expenditure share decreases with income.

Table 4A shows changes in Chinese urban household's average income from 2006 to 2015. During that timeframe, the average Chinese urban household income increased rapidly from about ¥3000 to nearly ¥8000. Table 4A also shows expenditure amounts, the proportion of meat expenditure, and the proportion of food expenditure from the four sample provinces. Note that the proportion of food expenditure decreased from 2006 to 2015 as income levels went up, which is consistent to Engel's law. The proportion of meat expenditure went up from 2006 to 2011, but went down again in 2015. However, the absolute amount of meat expenditure consistently increased during the same period. Given the stability of meat consumption from 2006 to 2011, the increase in meat expenditure proportion is mainly due to an increase in meat prices, especially pork. From 2011 to 2015, the decrease in the proportion of meat expenditure is due to a decrease in pork prices and a rapid increase in income levels.Comparing across provinces, we can see Guangdong and Shanghai have relatively higher level of income than the other two provinces. The absolute amount of expenditure on meats keeps increasing, and the proportion of expenditure on food goes down in general as income grows, which is consistent to Engle's law in all provinces. In Table 4B, we can see the same pattern across different income groups in Liaoning as we see in

Table 4A. Here, we can see that lower income group has higher proportion of income spent on food, and the proportion also decreases as income grows. This again is consistent with Engel's law.

Liu et al. (2009), show that in 2005, Chinese household's budget share of pork was 40%, poultry was 19%, beef was 11%, and mutton was 8%. While our study does have some differences from Liu et al. (2009), the proportion of the meat budget shares we reveal also show that pork is Chinese household's most-consumed meat, followed by poultry, beef, and mutton. Chen et al. (2015) show that in 2011, pork, beef, chicken, and mutton consumption among Chinese consumers was similar to what Liu et al. (2009) find, giving further credence to the statistics from UHS datasets.

Results

We estimate the AIDS model using the approaches described in the Methodology section, and then use our results of estimation to estimate the income elasticities as well as the Marshallian price elasticities of each meat. We report the parameter estimation of the AIDS model for the four provinces overall in Table A1 in the Appendix.

Income elasticities

Table 5A shows our estimated income elasticities for each kind of meat overall and in each province, while Table 5B shows the income elasticities for each income group in Liaoning. Here we adopt a two-stage budgeting approach to calculate the income elasticities. First, I estimate the income elasticities of broad commodity groups using the AIDS model and report the income elasticities of meats (we report corresponding t-statistics below the elasticities). Second, we use the AIDS model to estimate the expenditure elasticities of each kind of meat within the "Meats" group. Third, we use the expenditure elasticity of each meat to multiply the income elasticity of Meats to get the income elasticity of each meat. We report income elasticities and t-statistics of each meat and meats as a whole in Table 5A. We perform t-tests to explore changes in the income elasticities across years and across provinces. Horizontally, we use Italic numbers to indicate that the income elasticities are significantly different from the previous year at 5% level, and we use superscripts of the name initials of the provinces to indicate that the income elasticities are significantly different from those of the province that the superscripts indicate.[a]

From Table 5A and 5B, we can see that no matter across provinces, over years or across different income groups, pork's income elasticities are always below 1. This means pork is a necessity in China, and this finding is pretty stable. From Table 5B, pork income elasticities increased over years, and have generally increased with income. So after the outbreak of PED in 2011, the booming pork market and the increasing household income would contribute to the growth in China's pork demand.

In general, beef has income elasticities greater than 1, which indicates that mostly beef is a luxury good in China. However, we can see that in Shanghai and Sichuan, beef has approached becoming a necessity in 2011 moving back to a luxury good in 2015; while in Guangdong beef started as a necessity from 2006 to 2011, though its income elasticities kept increasing, and became a luxury good in 2015. In the case of Guangdong, we can see that from 2006 to 2011, its average household income level was much higher than the other three provinces, while its beef prices were

[a] For example, Liaoning's pork income elasticity in 2009 is *0.886* $^{\mathbf{sh,g,si}}$, which means it is significantly different from the income elasticities of Shanghai, Guangdong and Sichuan at 5% level in the same year.

not much higher than those in the other three provinces. So the relatively high income in Guangdong made its beef a necessity in 2006-2011. Also in 2015 the rapid increase in beef prices drove beef in Guangdong to become a luxury good. In Table 5B, we can see that in general, the income elasticities of beef are lower in high income group than those in middle and low income groups. This is consistent with our findings in Table 5A, Table 2B and Table 4A.

We can also see similar pattern change in mutton and chicken in 2009 to 2011 and 2011 to 2015 from Table 5A, this can also be explained by the relative changes in mutton prices and average household income similar to what we analyzed for beef. Generally speaking, mutton's income elasticities are greater than 1, so in general, mutton is a luxury good, but chicken's income elasticities are pretty close to 1. In Table 5B, we can also see that mutton and chicken in different income groups mostly follow similar consumption patterns as the whole country and they're mostly luxury goods. In Table 5A, we can see that the income elasticities of other meats are mostly smaller than 1. So generally speaking, other meats are necessities to Chinese consumers.

Our results of meat consumption pattern change over time are consistent with results from other studies in the literature. Gao, Wailes, and Cramer (1996), Chen et al. (2015), and Dong, Davis, and Stewart (2015) all show similar results, which include positive and statistically significant income or expenditure elasticities. However, due to systematic differences across the databases used, there are differences among income or expenditure elasticities reported. Likewise, it is also reasonable that our results of income elasticities have slight differences from previous studies due to systematic, time, and approach differences between the UHS database and the data they used. For example, Chen et al. (2015) report 2011 beef and mutton income elasticities as less than one, indicating they are necessities; however, our results show 2011 beef and mutton income elasticities are greater than one, indicating they are luxuries. Generally speaking, the trends in income elasticities of all kinds of meats were relatively flat and showed no sign of drastic increase or decrease.

Price Elasticities

Table 6A-6E and Table 7A-7E show us the Marshallian price elasticities by province and by income group in Liaoning respectively. Generally speaking, pork was price inelastic, with the most elastic estimates coming from Liaoning. As we combine the analysis on pork income elasticities and that on price elasticities, we can see that Liaoning's pork price elasticities are higher and its income elasticities are relatively lower. This means that in Liaoning, consumers have more substitutes for pork. We can see from Table 6A that in Liaoning, pork and beef are substitutes and they're mostly significant. This is reasonable because Liaoning is located next to Inner Mongolia, which is a major producer of beef. So the transportation cost of transiting beef from Inner Mongolia to Liaoning is relatively low. The availability of substitutes help explain why pork was relatively price elastic in Liaoning while inelastic in other provinces. In Table 7A, we can find consistent pork price elasticities pattern change as in Table 6A so heterogeneity in income does not play a big role in pork price elasticities. Similarly in Table 6B, we can see beef was also price inelastic in general, while Liaoning still have high price elasticities compared to other provinces, since they have more options to substitute beef consumption with pork.

In Table 6C, we can observe that the price elasticities of mutton in Liaoning are relatively low, so in Liaoning, mutton was mostly a necessity, while in the other provinces it is a luxury good. This is consistent to the fact that in northeastern China, mutton is more commonly consumed than the southern part of the country, especially during winter. We can see this in Table 2C, where Liaoning's consumption of mutton is much higher than the other three provinces. In 2015, mutton was mostly price elastic. This can be explained by the rapid increase in mutton price and the relatively moderate increase in average household income displayed in Table 2C and Table 4A. In Table 7C, there are no significant differences of mutton price elasticities among the income groups, so we may conclude heterogeneity in household income does not have an effect on mutton price elasticities. In Table 6D and Table 6E, we can see that the chicken and other meats price elasticities are always below 1 so chicken and other meats are both price inelastic. Table 2A-2E display that the prices of beef, mutton and chicken increase rapidly over the years, and Table 6A-6E indicate that the Mashallian price elasticities of beef, mutton, and chicken all increase in general and reach a relatively high level in 2015, thus the increase in prices reduce the expenditure shares of beef, mutton and chicken by much. Although pork and other meats are normal goods and beef, mutton and chicken are luxury goods, as household income increases shown in Table 4A and 4B, pork still captures a larger share in meat expenditure.

Generally speaking, our Marshallian price elasticities are similar to relevant previous studies—all of the own-price elasticities are negative and statistically significant, and most of the own-price elasticities are less than one in magnitude. Our results are consistent with Wang et al. (1998), Chen et al. (2015), and Gao, Wailes, and Cramer (1996).

As table 6A-6E display, the Marshallian cross-price elasticities for pork and other meats and beef and chicken are both stable. These two groups had statistically significant Marshallian cross-price elasticities and an unchanged relationship over the years. The Marshallian cross-price elasticities of the other meat groups are statistically significant, but might change over the sample years, which reveals an unstable relationship of consumption between the two meats within the group. For example, in 2006 pork and beef were substitutes, but in 2009 they became complements, which was still true in 2015. This reveals that over the years, Chinese consumer's preferences changed. In 2006, Chinese consumers substituted pork and beef depending on availability and price; however, in 2009 and 2015, they were willing to consume more pork and beef together.

In Table 8, we report the Hicksian Price elasticities of pork, beef, mutton, chicken and other meats covering all the four provinces sample. We can see they have similar pattern as the corresponding Marshallian Price elasticities.

Conclusion

In this study, we use the Amemiya-Tobin approach to estimate the AIDS model and calculate the corresponding demand elasticities. Our results show that pork was mostly a necessity in China, while beef and mutton were mostly luxury goods. Chicken's income elasticities were close to 1 and it varied slightly across different years, and other meats were always a necessity. Concerning income and provincial heterogeneity effects, pork income elasticities increased with income in 2006 and in 2009, however, they began to decline when household income reached higher levels in 2011 and 2015, indicating a change in pork preferences. Beef income elasticities show similar change pattern to pork among different income groups. Mutton's income elasticities pattern change were pretty similar to what we analyzed for beef, and chicken was a necessity rather than a luxury good in Liaoning in 2015 might be explained by the low chicken price there in 2015.

From our analysis of the price elasticities of meats, we can see that the Marshallian price elasticities of pork in Liaoning was relatively high and sometimes they were price elastic, while in other provinces pork was always price inelastic. The low transportation cost made availability of substitutes higher, thus pork was more price elastic in Liaoning than the other three provinces. Heterogeneity across income groups does not play a big role in pork price elasticities because pork price elasticities follow the same change pattern among different income groups. In Liaoning, mutton is a necessity because in northeastern China, consumers are more inclined to eat mutton in the winter. Chicken and other meats were both price inelastic in China.

Our results show that when the Chinese pork market recovered from the PED outbreak in 2011, the price of pork declined and the income elasticity of pork went down, indicating that the demand for pork was driven up by the booming market and the rapidly increasing income growth. Also, beef and mutton became luxury goods and consumption of those items transitioned to pork, which further increased the scale of pork demand in China. The market events of 2019 are similar to that of 2011— both years saw outbreaks of swine disease. Although we do not have access to 2019 data, we still expect to see the pork market boom again after the ASF outbreak in China is under control. Hence, not only will the current ASF outbreak bring growth opportunities for the U.S. pork export industry, but I also expect China's consumer demand for pork to continue to grow due to the increase in household income. Thus, if China and the United States continue successful negotiations and China exempts duties on U.S. pork exports, we will see great potential for the U.S. pork export industry.

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Figures and Tables

Table 1. Meat Production in China, 2000–2016 (Metric Tons)

Year	Pork	Beef	Chicken	Total
2000	39,660,000	5,131,000	9,269,000	54,060,000
2001	40,517,000	5,086,000	9,278,000	54,881,000
2002	41,231,000	5,219,000	9,558,000	56,008,000
2003	42,386,000	5,425,000	9,898,000	57,709,000
2004	43,410,000	5,604,000	9,998,000	59,012,000
2005	45,553,000	5,681,000	10,200,000	61,434,000
2006	46,505,000	5,767,000	10,350,000	62,622,000
2007	42,878,000	6,134,000	11,291,000	60,303,000
2008	46,205,000	6,132,000	11,840,000	64,177,000
2009	48,908,000	6,355,000	12,100,000	67,363,000
2010	50,712,000	6,531,000	12,550,000	69,793,000
2011	50,604,000	6,475,000	13,200,000	70,279,000
2012	53,427,000	6,623,000	13,700,000	73,750,000
2013	54,930,000	6,730,000	13,350,000	75,010,000
2014	56,710,000	6,890,000	13,000,000	76,600,000
2015	56,375,000	6,750,000	13,025,000	76,150,000
2016	56,500,000	6,785,000	13,100,000	76,385,000

Source: FAS/USDA

Table 2A. Pork Consumption, Prices, and Expenditure Share Statistics in China by Province

Pork	Statistics	2006	2009	2011	2015
Overall	Average household consumption in the four sample provinces (kg/day)	0.18	0.19	0.19	0.29
	Average household consumption at the national urban level (kg/day)	0.17	0.18	0.17	0.28
	Average prices (¥/kg)	13.24	20.75	27.95	27.10
	Meat expenditure share (percentage)	52.90%	48.80%	51.90%	56.30%
Liaoning	Average household consumption in Liaoning (kg/day)	0.14	0.13	0.12	0.17
	Average prices (¥/kg)	12.04	19.13	26.24	22.49
	Meat expenditure share (percentage)	49.60%	46.40%	51.50%	54.80%
Shanghai	Average household consumption Shanghai (kg/day)	0.16	0.15	0.24	0.19
	Average prices (¥/kg)	13.73	20.79	30.95	29.05
	Meat expenditure share (percentage)	52.60%	45.90%	48.80%	47.10%
Guangdong	Average household consumption in Guangdong (kg/day)	0.27	0.27	0.27	0.35
	Average prices (¥/kg)	16.85	24.33	31.15	29.36
	Meat expenditure share (percentage)	54.20%	50.70%	51.00%	54.10%
Sichuan	Average household consumption in Sichuan (kg/day)	0.22	0.27	0.24	0.23
	Average prices (¥/kg)	11.43	24.33	26.05	25.19
	Meat expenditure share (percentage)	58.70%	56.60%	57.60%	66.90%

Source: 2006, 2009, 2011 UHS data and 2015 and 2007, 2010, 2012, and 2016 China Statistical Year Book.
Note: Average household consumption at the national level is calculated from the China Statistical Year Book, which only contains consumption data for poultry (not just chicken). The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 2B. Beef Consumption, Prices, and Expenditure Share Statistics in China by Province

Beef	Statistics	2006	2009	2011	2015
Overall	Average household consumption in the four sample provinces (kg/day)	0.02	0.02	0.02	0.02
	Average household consumption at the national urban level (kg/day)	0.02	0.02	0.02	0.02
	Average prices (¥/kg)	19.44	31.95	37.24	61.06
	Meat expenditure share (percentage)	8.50%	8.90%	9.40%	7.70%
Liaoning	Average household consumption in Liaoning (kg/day)	0.03	0.03	0.02	0.02
	Average prices (¥/kg)	17.29	30.83	35.31	57.89
	Meat expenditure share (percentage)	14.50%	17.20%	13.50%	12.50%
Shanghai	Average household consumption Shanghai (kg/day)	0.01	0.01	0.02	0.02
	Average prices (¥/kg)	21.11	31.74	41.77	62.94
	Meat expenditure share (percentage)	6.00%	5.40%	6.30%	9.20%
Guangdong	Average household consumption in Guangdong (kg/day)	0.02	0.02	0.02	0.02
	Average prices (¥/kg)	22.69	35.95	41.73	64.65
	Meat expenditure share (percentage)	5.70%	5.80%	6.10%	5.60%
Sichuan	Average household consumption in Sichuan (kg/day)	0.02	0.02	0.02	0.01
	Average prices (¥/kg)	16.78	35.95	33.25	57.45
	Meat expenditure share (percentage)	6.00%	6.60%	7.40%	5.30%

Source: 2006, 2009, 2011 UHS data and 2015 and 2007, 2010, 2012, and 2016 China Statistical Year Book.
Note: Average household consumption at the national level is calculated from the China Statistical Year Book, which only contains consumption data for poultry (not just chicken). The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 2C. Mutton Consumption, Prices, and Expenditure Share Statistics in China by Province

Mutton	Statistics	2006	2009	2011	2015
Overall	Average household consumption in the four sample provinces (kg/day)	0.01	0.01	0.01	0.01
	Average household consumption at the national urban level (kg/day)	0.01	0.01	0.01	0.01
	Average prices (¥/kg)	19.92	32.55	39.88	68.11
	Meat expenditure share (percentage)	3.90%	3.70%	3.30%	3.30%
Liaoning	Average household consumption in Liaoning (kg/day)	0.02	0.02	0.01	0.01
	Average prices (¥/kg)	18.3	27.63	34.50	58.92
	Meat expenditure share (percentage)	9.20%	8.80%	6.00%	7.40%
Shanghai	Average household consumption Shanghai (kg/day)	0.005	0.005	0.005	0.009
	Average prices (¥/kg)	20.62	31.22	45.32	72.04
	Meat expenditure share (percentage)	2.10%	2.40%	1.70%	4.20%
Guangdong	Average household consumption in Guangdong (kg/day)	0.005	0.005	0.006	0.006
	Average prices (¥/kg)	24.13	36.66	49.71	73.46
	Meat expenditure share (percentage)	1.50%	1.40%	1.50%	1.70%
Sichuan	Average household consumption in Sichuan (kg/day)	0.002	0.005	0.003	0.003
	Average prices (¥/kg)	17.93	28.66	40.46	59.14
	Meat expenditure share (percentage)	9.00%	1.00%	1.00%	1.30%

Source: 2006, 2009, 2011 UHS data and 2015 and 2007, 2010, 2012, and 2016 China Statistical Year Book.
Note: Average household consumption at the national level is calculated from the China Statistical Year Book, which only contains consumption data for poultry (not just chicken). The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 2D. Chicken Consumption, Prices, and Expenditure Share Statistics in China by Province

Chicken	Statistics	2006	2009	2011	2015
Overall	Average household consumption in the four sample provinces (kg/day)	0.05	0.06	0.06	0.05
	Average household consumption at the national urban level (kg/day)	0.07	0.09	0.09	0.08
	Average prices (¥/kg)	13.57	18.89	23.22	26.81
	Meat expenditure share (percentage)	13.70%	14.30%	13.10%	11.60%
Liaoning	Average household consumption in Liaoning (kg/day)	0.03	0.04	0.04	0.02
	Average prices (¥/kg)	11.35	16.22	18.22	21.04
	Meat expenditure share (percentage)	9.80%	10.80%	9.40%	7.50%
Shanghai	Average household consumption Shanghai (kg/day)	0.05	0.06	0.1	0.06
	Average prices (¥/kg)	13.66	18.49	26.55	28.86
	Meat expenditure share (percentage)	15.00%	14.00%	18.10%	12.20%
Guangdong	Average household consumption in Guangdong (kg/day)	0.1	0.12	0.12	0.12
	Average prices (¥/kg)	17.06	21.87	26.75	30.09
	Meat expenditure share (percentage)	19.60%	20.40%	19.50%	17.10%
Sichuan	Average household consumption in Sichuan (kg/day)	0.04	0.12	0.05	0.03
	Average prices (¥/kg)	14.54	21.87	26.52	27.74
	Meat expenditure share (percentage)	13.10%	12.90%	11.50%	8.60%

Source: 2006, 2009, 2011 UHS data and 2015 and 2007, 2010, 2012, and 2016 China Statistical Year Book.
Note: Average household consumption at the national level is calculated from the China Statistical Year Book, which only contains consumption data for poultry (not just chicken). The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 2E. Other Meats Consumption, Prices, and Expenditure Share Statistics in China by Province

Other Meats	Statistics	2006	2009	2011	2015
Overall	Average household consumption in the four sample provinces (kg/day)	0.05	0.08	0.08	0.08
	Average prices (¥/kg)	19.7	26.26	30.19	33.06
	Meat expenditure share (percentage)	20.90%	24.30%	22.30%	21.10%
Liaoning	Average household consumption in Liaoning (kg/day)	0.04	0.04	0.05	0.04
	Average prices (¥/kg)	16.1	22.29	26.52	29.04
	Meat expenditure share (percentage)	16.90%	16.80%	19.70%	17.80%
Shanghai	Average household consumption Shanghai (kg/day)	0.05	0.05	0.05	0.09
	Average prices (¥/kg)	22.53	28.65	32.57	37.24
	Meat expenditure share (percentage)	24.40%	32.30%	25.10%	27.30%
Guangdong	Average household consumption in Guangdong (kg/day)	0.12	0.13	0.11	0.13
	Average prices (¥/kg)	23.71	32.93	36.44	34.53
	Meat expenditure share (percentage)	18.90%	21.80%	21.90%	21.50%
Sichuan	Average household consumption in Sichuan (kg/day)	0.02	0.05	0.08	0.05
	Average prices (¥/kg)	16.51	23.02	29.81	28.94
	Meat expenditure share (percentage)	21.30%	22.90%	22.50%	17.90%

Source: 2006, 2009, 2011 UHS data and 2015 and 2007, 2010, 2012, and 2016 China Statistical Year Book.
Note: Average household consumption at the national level is calculated from the China Statistical Year Book, which only contains consumption data for poultry (not just chicken). The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 3. Meat Consumption, and Expenditure Share Statistics in Liaoning by Household Income

Pork	Statistics	2006	2009	2011	2015
Low Income	Average household consumption (kg/day)	0.12	0.12	0.09	0.16
	Meat expenditure share (percentage)	53.00%	48.20%	55.80%	65.90%
Middle Income	Average household consumption (kg/day)	0.14	0.13	0.12	0.18
	Meat expenditure share (percentage)	49.40%	45.90%	50.90%	52.40%
High Income	Average household consumption (kg/day)	0.15	0.14	0.13	0.19
	Meat expenditure share (percentage)	46.40%	42.80%	47.80%	46.40%
Beef					
Low Income	Average household consumption (kg/day)	0.03	0.03	0.02	0.01
	Meat expenditure share (percentage)	15.00%	16.70%	12.30%	8.20%
Middle Income	Average household consumption (kg/day)	0.03	0.03	0.03	0.02
	Meat expenditure share (percentage)	14.30%	17.60%	13.60%	12.90%
High Income	Average household consumption (kg/day)	0.04	0.04	0.03	0.03
	Meat expenditure share (percentage)	14.20%	18.40%	14.50%	16.30%
Mutton					
Low Income	Average household consumption (kg/day)	0.01	0.01	0.01	0.01
	Meat expenditure share (percentage)	8.60%	8.20%	5.30%	5.40%
Middle Income	Average household consumption (kg/day)	0.02	0.02	0.01	0.01
	Meat expenditure share (percentage)	9.10%	8.70%	6.20%	8.10%
High Income	Average household consumption (kg/day)	0.02	0.02	0.01	0.02
	Meat expenditure share (percentage)	10.00%	9.90%	6.50%	8.70%
Chicken					
Low Income	Average household consumption (kg/day)	0.03	0.04	0.03	0.01
	Meat expenditure share (percentage)	10.10%	11.10%	9.90%	6.80%
Middle Income	Average household consumption (kg/day)	0.03	0.04	0.04	0.03
	Meat expenditure share (percentage)	9.60%	10.70%	9.50%	7.80%
High Income	Average household consumption (kg/day)	0.04	0.04	0.04	0.03
	Meat expenditure share (percentage)	9.70%	10.30%	8.80%	7.80%
Other Meats					
Low Income	Average household consumption (kg/day)	0.02	0.02	0.03	0.02
	Meat expenditure share (percentage)	13.30%	15.90%	16.80%	13.70%
Middle Income	Average household consumption (kg/day)	0.04	0.04	0.05	0.05
	Meat expenditure share (percentage)	17.60%	17.10%	19.80%	18.80%
High Income	Average household consumption (kg/day)	0.05	0.05	0.06	0.06
	Meat expenditure share (percentage)	19.60%	18.60%	22.50%	20.80%

Source: 2006, 2009, 2011 UHS data and 2015 and 2007, 2010, 2012, and 2016 China Statistical Year Book.
Note: Average household consumption at the national level is calculated from the China Statistical Year Book, which only contains consumption data for poultry (not just chicken). The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 4A. Average Monthly Household Income and Expenditures in Four Sample Chinese Provinces

		2006	2009	2011	2015
Overall	Average monthly household income at the national urban level (¥)	3106.47	4508.34	5488.8	8058.65
	Average monthly household income in the four sample provinces (¥)	3184.17	4668.42	6000.67	7911.61
	Percentage change compared to 2006 (in the four sample provinces)	0%	46.61%	88.45%	148.47%
	Proportion of average monthly household income spent on meats in the four sample provinces	4.30%	5.17%	5.22%	4.55%
	Average monthly household expenditure on meats in the four sample provinces (¥)	136.92	241.36	313.23	359.98
	Proportion of average monthly household income spent on foods in the four sample provinces	16.17%	15.97%	15.78%	14.45%
Liaoning	Average monthly household income (¥)	2499.27	3737.6	4603.26	6069.19
	Percentage change compared to 2006	0%	49.55%	84.18%	142.84%
	Proportion of average monthly household income spent on meats	4.18%	4.35%	3.90%	3.53%
	Average monthly household expenditure on meats (¥)	104.42	162.69	179.75	214.19
	Proportion of average monthly household income spent on foods	20.31%	17.57%	15.32%	14.03%
Shanghai	Average monthly household income (¥)	3519.08	5030.23	8304.36	9015.33
	Percentage change compared to 2006	0%	42.94%	135.98%	156.18%
	Proportion of average monthly household income spent on meats	4.68%	5.56%	5.74%	4.83%
	Average monthly household expenditure on meats (¥)	164.69	279.68	476.67	435.44
	Proportion of average monthly household income spent on foods	15.68%	15.35%	15.22%	14.04%
Guangdong	Average monthly household income (¥)	4664.53	6110.89	7862.58	9328.74
	Percentage change compared to 2006	0%	41.10%	90.88%	132.54%
	Proportion of average monthly household income spent on meats	4.75%	5.82%	5.96%	5.18%
	Average monthly household expenditure on meats (¥)	221.57	355.65	468.61	483.23
	Proportion of average monthly household income spent on foods	15.53%	15.14%	14.98%	13.96%
Sichuan	Average monthly household income (¥)	2463.17	3673.36	4700.4	6564.83
	Percentage change compared to 2006	0%	34.39%	63.57%	116.55%
	Proportion of average monthly household income spent on meats	4.13%	5.01%	5.23%	4.96%
	Average monthly household expenditure on meats (¥)	101.73	184.04	245.83	325.62
	Proportion of average monthly household income spent on foods	17.08%	16.63%	16.35%	15.39%

Source: 2006, 2009, 2011 and 2015 UHS data and 2007, 2010, 2012 and 2016 China Statistical Year Book.
Note: The four sample provinces are Liaoning, Shanghai, Guangdong, and Sichuan.

Table 4B. Average Monthly Household Income and Expenditures in Liaoning

		2006	2009	2011	2015
Low Income	Average monthly household income (¥)	1228.59	2012.67	2464.23	2886.73
	Percentage change compared to 2006	0%	63.82%	100.57%	134.96%
	Proportion of average monthly household income spent on meats	6.53%	5.87%	5.26%	5.37%
	Average monthly household expenditure on meats (¥)	80.27	118.19	129.59	155.12
	Proportion of average monthly household income spent on foods	30.66%	23.97%	19.95%	18.30%
Middle Income	Average monthly household income (¥)	2187.67	3185.26	3806.7	4301.94
	Percentage change compared to 2006	0%	81.20%	131.78%	172.09%
	Proportion of average monthly household income spent on meats	4.93%	5.35%	5.02%	5.31%
	Average monthly household expenditure on meats (¥)	107.88	170.40	190.99	228.57
	Proportion of average monthly household income spent on foods	23.26%	20.79%	18.79%	19.89%
High Income	Average monthly household income (¥)	4076.97	6283.37	7988.18	12543.02
	Percentage change compared to 2006	0%	179.59%	318.35%	689.09%
	Proportion of average monthly household income spent on meats	3.08%	3.18%	2.74%	2.23%
	Average monthly household expenditure on meats (¥)	125.53	199.57	219.08	279.30
	Proportion of average monthly household income spent on foods	15.63%	13.13%	11.37%	9.32%

Source: 2006, 2009, 2011 and 2015 UHS data and 2007, 2010, 2012 and 2016 China Statistical Year Book.

Table 5A. Income Elasticities of Meats in China

Income Elasticities		2006	2009	2011	2015
Overall	Meats	0.939	*0.967*	*0.979*	*0.976*
		(187.80)	(241.75)	(244.75)	(325.33)
	Pork	0.924	*0.936*	*0.967*	*0.897*
		(196.80)	*(242.00)*	*(247.00)*	*(306.33)*
	Beef	1.089	*1.135*	*1.084*	*1.242*
		(72.50)	*(83.86)*	*(79.07)*	*(90.93)*
	Mutton	1.161	1.153	*1.131*	*1.234*
		(58.86)	(59.60)	(52.50)	(45.14)
	Chicken	1.029	*1.001*	*0.999*	*1.092*
		(109.60)	(129.38)	(127.50)	(159.86)
	Other Meats	0.814	0.919	*0.908*	*0.986*
		(86.70)	(118.75)	(127.78)	(101.00)
Liaoning	Meats	1.006	*1.031*	1.025	*0.989*
		(100.60)	(114.56)	(196.20)	(164.83)
	Pork	0.861 [sh,si]	*0.886* [sh,g,si]	*0.981* [sh,g,si]	*0.972* [sh,g,si]
		(85.60)	(85.90)	(136.71)	(122.88)
	Beef	1.228 [sh]	*1.291* [sh,g,si]	*1.159* [sh,g,si]	*1.207* [g,si]
		(46.96)	(59.62)	(59.53)	(55.45)
	Mutton	1.325 [sh,g,si]	1.353 [sh,g,si]	1.224 [sh,g,si]	*1.199* [sh,si]
		(47.04)	(50.46)	(47.76)	(41.79)
	Chicken	1.116 [sh,g,si]	*1.015* [sh,g,si]	*1.038* [sh,g,si]	*0.868* [sh]
		(48.22)	(49.20)	(59.59)	(29.44)
	Other Meats	1.003 [sh,si]	1.009 [sh,g,si]	*0.981* [sh,g,si]	*0.887* [sh,g]
		(45.32)	(44.5)	(63.80)	(47.21)
Shanghai	Meats	0.955	0.955	0.935	*0.909*
		(106.11)	(119.38)	(155.83)	(113.63)
	Pork	0.989 [g,si]	*0.974* [g,si]	0.962 [g,si]	0.878 [g,si]
		(148.00)	(145.71)	(171.5)	(138.00)
	Beef	1.057	*1.084* [g,si]	*0.963* [g,si]	*1.042* [g,si]
		(38.17)	(39.14)	(57.22)	(54.57)
	Mutton	1.116 [g,si]	0.946 [g]	*0.827* [si]	*1.04* [g,si]
		(27.83)	(23.60)	(28.55)	(32.69)
	Chicken	1.063 [g,si]	*1.046* [g,si]	*0.991* [g,si]	*1.072* [g,si]
		(85.62)	(84.23)	(106.00)	(90.69)
	Other Meats	0.776 [g,si]	0.868 [g,si]	*0.842* [si]	*0.824* [g,si]
		(62.54)	(82.64)	(81.82)	(75.58)
Guangdong	Meats	0.873	0.963	*0.955*	*0.883*
		(67.15)	(192.6)	(191.00)	(176.60)
	Pork	0.867 [si]	0.952	*0.957* [si]	*0.793* [si]
		(76.38)	(165.67)	(166.17)	(149.67)
	Beef	0.930 [si]	*0.996* [si]	*0.991* [si]	*1.046* [si]
		(22.19)	(49.24)	(49.43)	(26.93)
	Mutton	0.904 [si]	0.895 [si]	*0.871* [si]	*1.038* [si]
		(12.78)	(29.03)	(27.64)	(9.19)
	Chicken	0.952	*0.965* [si]	*0.992* [si]	*1.019*
		(45.42)	(91.09)	(94.45)	(96.17)
	Other Meats	0.789 [si]	0.97 [si]	*0.924* [si]	*0.947* [si]
		(33.48)	(83.92)	(74.46)	(48.73)

Table 5A. Continued

	Meats	0.938	*0.980*	*0.978*	*1.037*
		(78.17)	(163.33)	(163.00)	(325.33)
	Pork	0.934	*0.953*	*0.997*	*0.974*
		(99.60)	(108.00)	(127.38)	(234.75)
	Beef	1.17	*1.102*	*0.981*	*1.349*
		(31.97)	(37.47)	(34.59)	(41.97)
Sichuan	**Mutton**	1.211	1.128	*0.798*	*1.434*
		(14.67)	(18.56)	(12.95)	(14.26)
	Chicken	0.947	0.956	1.018	1.213
		(40.40)	(54.17)	(65.06)	(68.82)
	Other Meats	0.865	1.019	*0.916*	*1.067*
		(40.09)	(52.00)	(58.56)	(57.17)

Source: 2006, 2009, 2011 and 2015 UHS data.

Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "sh" means Liaoning has significant difference with that in Shanghai; (sh=Shanghai, g=Guangdong, si=Sichuan)

Table 5B. Income Elasticities of Meats in Liaoning by Household Income Group

Income Elasticities		2006	2009	2011	2015
Low Income	Meats	1.086	*1.006*	*1.037*	*1.004*
		(48.41)	(100.6)	(54.58)	(83.67)
	Pork	0.847 ^{h}	*0.913* ^{m,h}	0.908 ^{m,h}	*0.964* ^{m,h}
		(56.28)	(74.49)	(85.74)	(93.28)
	Beef	1.343	*1.232* ^{m,h}	*1.154* ^{m,h}	*1.109* ^{m,h}
		(27.60)	(44.77)	(41.48)	(23.46)
	Mutton	1.377	*1.338* ^{m,h}	*1.199* ^{m,h}	*1.206* ^{m,h}
		(38.79)	(42.06)	(36.16)	(32.41)
	Chicken	1.180	1.124 ^{m}	*1.020* ^{m,h}	0.634 ^{m,h}
		(34.97)	(40.05)	(44.22)	(26.73)
	Other Meats	1.244 ^{m,h}	1.063 ^{m,h}	1.046 ^{m,h}	0.698 ^{m,h}
		(29.86)	(42.18)	(34.52)	(22.69)
Middle Income	Meats	1.061	*0.997*	1.129	*1.130*
		(20.80)	(241.75)	(22.20)	(325.33)
	Pork	0.858 ^{h}	*0.874* ^{h}	*1.042* ^{h}	*0.984* ^{h}
		(51.46)	(42.16)	(52.94)	(57.25)
	Beef	1.417	*1.337* ^{h}	*1.293* ^{h}	*1.297* ^{h}
		(31.59)	(33.67)	(35.47)	(29.85)
	Mutton	1.374	1.372 ^{h}	*1.264* ^{h}	*1.233* ^{h}
		(25.38)	(23.41)	(21.37)	(22.15)
	Chicken	1.113	*1.021*	*1.038* ^{h}	*0.924*
		(26.81)	(27.57)	(28.75)	(26.54)
	Other Meats	0.989 ^{h}	0.945 ^{h}	0.927 ^{h}	1.029
		(25.28)	(22.98)	(27.36)	(26.21)
High Income	Meats	0.997	0.953	*1.051*	*1.028*
		(34.38)	(41.43)	(47.77)	(46.73)
	Pork	0.915	*0.897*	*0.956*	*0.946*
		(48.73)	(52.18)	(74.24)	(65.03)
	Beef	1.164	*1.196*	*1.136*	*1.213*
		(29.16)	(37.24)	(39.64)	(42.15)
	Mutton	1.308	1.261	*1.229*	*1.133*
		(28.62)	(27.13)	(24.33)	(28.02)
	Chicken	1.079	*0.968*	*1.081*	*0.866*
		(27.91)	(27.43)	(28.74)	(26.47)
	Other Meats	0.747	0.762	*0.862*	*0.874*
		(21.22)	(25.67)	(32.69)	(31.58)

Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "m" means the elasticity is significantly different between low and middle income household; (m=middle household income group, h=high household income group).

Table 6A. Marshallian Price Elasticities of Pork in China

Marshallian Price Elasticities		**2006**	**2009**	**2011**	**2015**
Overall	**Pork Price**	**-0.914**	***-0.802***	***-0.853***	***-0.782***
		(-45.70)	**(-44.56)**	**(-40.62)**	**(-65.17)**
	Beef Price	0.054	-0.029	0.002	-0.019
		(3.60)	(-2.23)	(0.11)	(-2.38)
	Mutton Price	0.006	0.015	-0.010	0.020
		(0.43)	(1.36)	(-0.91)	(2.86)
	Chicken Price	-0.012	-0.044	0.008	-0.010
		(-0.92)	(-3.67)	(0.67)	(-1.25)
	Other Meats Price	-0.118	-0.107	-0.136	-0.127
		(-13.11)	(-11.89)	(-11.33)	(-21.17)
Liaoning	**Pork Price**	**-0.991**^{sh,si}	***-1.048***^{sh,g,si}	***-0.932***^{sh,g,si}	***-1.046***^{sh,g,si}
		(-23.60)	**(-21.39)**	**(-24.53)**	**(-30.76)**
	Beef Price	0.220	0.213	0.044	0.036
		(5.12)	(3.87)	(1.26)	(1.09)
	Mutton Price	-0.031	0.067	-0.017	0.083
		(-0.89)	(1.43)	(-0.68)	(2.52)
	Chicken Price	0.007	-0.040	0.025	-0.001
		(0.30)	(-1.67)	(1.47)	(-0.005)
	Other Meats Price	-0.061	-0.050	-0.077	-0.055
		(-2.77)	(-1.92)	(-3.67)	(-3.06)
Shanghai	**Pork Price**	**-0.963**^{g,si}	***-0.745***^{g,si}	**-0.590**^{g,si}	**-0.721**^{g,si}
		(-32.10)	**(-23.28)**	**(-17.35)**	**(-26.70)**
	Beef Price	0.031	-0.079	-0.011	-0.006
		-1.48	(-4.16)	(-0.52)	(-0.35)
	Mutton Price	0.048	0.015	0.008	0.012
		-2.29	-0.79	-0.53	-0.92
	Chicken Price	-0.033	-0.066	-0.058	-0.042
		(-1.65)	(-3.30)	(-2.15)	(-2.10)
	Other Meats Price	-0.120	-0.146	-0.378	-0.208
		(-10.00)	(-9.73)	(-18.00)	(-13.87)
Guangdong	**Pork Price**	**-0.864**^{si}	**-0.690**	***-0.703***^{si}	***-0.601***^{si}
		(-16.54)	**(-21.56)**	**(-20.09)**	**(-27.32)**
	Beef Price	0.006	0.003	0.008	-0.043
		(0.20)	(0.18)	(0.40)	(-3.91)
	Mutton Price	0.019	0.022	0.018	0.009
		(0.61)	(1.47)	(1.20)	(0.75)
	Chicken Price	0.012	-0.245	-0.117	-0.032
		(0.27)	(-9.07)	(-3.90)	(-1.78)
	Other Meats Price	-0.166	-0.084	-0.203	-0.233
		(-6.07)	(-4.00)	(-8.46)	(-17.92)

Table 6A. Continued

Sichuan	**Pork Price**	**-0.839**	***-0.803***	***-0.663***	***-0.816***
		(-17.48)	**(-22.94)**	**(-13.81)**	**(-35.48)**
	Beef Price	-0.004	-0.013	-0.054	-0.031
		(0.13)	(-0.43)	(-1.38)	(-2.07)
	Mutton Price	0.005	-0.009	-0.007	-0.002
		-0.17	(-0.50)	(-0.47)	(-0.15)
	Chicken Price	-0.067	-0.059	-0.197	-0.037
		(-2.16)	(-2.03)	(-6.35)	(-2.31)
	Other Meats Price	-0.090	-0.087	-0.098	-0.052
		(-4.74)	(7.25)	(-4.90)	(-5.20)

Source: 2006, 2009, 2011 and 2015 UHS data.

Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year at 5% level. The superscript means it is significantly difference from province at 5% level, eg: superscript "sh" means Liaoning has significant difference with that in Shanghai; (sh=Shanghai, g=Guangdong, si=Sichuan).

Table 6B. Marshallian Price Elasticities of Beef in China

Marshallian Price Elasticities		2006	2009	2011	2015
Overall	Pork Price	0.247	-0.261	-0.050	-0.338
		(3.53)	(-4.42)	(-0.70)	(-7.51)
	Beef Price	**-0.758**	***-0.679***	***-0.890***	***-0.841***
		(-10.94)	**(-9.02)**	**(-15.08)**	**(-29.00)**
	Mutton Price	-0.069	-0.004	-0.002	-0.087
		(-1.41)	(-0.11)	(-0.05)	(-3.22)
	Chicken Price	-0.305	-0.147	-0.125	-0.099
		(-6.78)	(-3.77)	(-3.13)	(-3.09)
	Other Meats Price	-0.476	-0.384	-0.040	0.093
		(-0.032)	(-13.24)	(-0.98)	(3.72)
Liaoning	Pork Price	0.571	0.390	0.079	0.025
		(5.29)	(3.75)	(0.81)	(0.28)
	Beef Price	**-1.210**[sh]	***-1.026***[sh,g,si]	***-1.071***[sh,g,si]	***-1.076***[g,si]
		(-11.00)	**(-8.84)**	**(-11.90)**	**(-12.81)**
	Mutton Price	-0.233	-0.380	-0.103	-0.088
		(-2.56)	(-3.80)	(-1.63)	(-1.04)
	Chicken Price	-0.173	0.008	0.028	-0.085
		(-2.88)	(0.16)	(0.64)	(-1.60)
	Other Meats Price	-0.175	-0.243	-0.063	0.003
		(-3.07)	(-4.34)	(-1.17)	(0.07)
Shanghai	Pork Price	0.237	-0.726	-0.089	-0.116
		(-1.80)	(-5.72)	(-0.83)	(-1.55)
	Beef Price	**-0.732**	***-0.556***[g,si]	***-0.452***[g,si]	***-1.047***[g,si]
		(-7.52)	**(-6.95)**	**(-6.85)**	**(-22.28)**
	Mutton Price	-0.100	0.165	0.070	-0.114
		(-1.09)	(2.17)	(1.43)	(-3.08)
	Chicken Price	-0.218	0.019	-0.674	0.090
		(-2.45)	-0.24	(-7.84)	(1.61)
	Other Meats Price	-1.096	-1.149	0.115	0.041
		(-18.90)	(-17.95)	(-1.77)	(0.93)
Guangdong	Pork Price	0.021	0.003	0.042	-0.565
		(0.11)	(0.02)	(0.35)	(-5.82)
	Beef Price	**-0.591**	***-0.593***[si]	***-0.442***[si]	***-0.537***[si]
		(-5.37)	**(-8.85)**	**(-6.31)**	**(-10.74)**
	Mutton Price	-0.001	0.016	0.081	-0.078
		(-0.01)	(0.28)	(1.56)	(-1.42)
	Chicken Price	-0.580	-0.504	-0.841	-0.350
		(-3.58)	-4.89	(-8.17)	(-4.43)
	Other Meats Price	0.086	0.045	0.122	0.344
		(0.83)	(0.55)	(1.51)	(5.29)
Sichuan	Pork Price	-0.186	-0.199	-0.410	-0.632
		(-1.02)	(-1.70)	(-2.20)	(-4.79)
	Beef Price	**-0.599**	***-0.925***	***-0.882***	***-0.583***
		(-4.95)	**(-9.16)**	**(-5.80)**	**(-6.94)**
	Mutton Price	0.062	0.062	0.107	0.015
		(0.54)	(1.05)	(1.81)	(0.20)
	Chicken Price	-0.448	-0.471	0.365	-0.083
		(-3.76)	(-4.91)	(3.04)	(-0.89)
	Other Meats Price	-0.076	0.409	-0.184	-0.017
		(-1.06)	(9.98)	(-2.33)	(-0.28)

Source: 2006, 2009, 2011 and 2015 UHS data.

Table 6C. Marshallian Price Elasticities of Mutton in China

Marshallian Price Elasticities		2006	2009	2011	2015
Overall	Pork Price	-0.057	0.089	-0.237	0.136
		(-0.64)	-1.01	(-2.10)	-2.06
	Beef Price	-0.156	-0.010	-0.009	-0.200
		(-2.40)	(-0.16)	(-0.10)	(-4.55)
	Mutton Price	**-0.745**	**-0.773**	***-0.783***	***-1.039***
		(-11.83)	**(-13.80)**	**(-13.05)**	**(-26.64)**
	Chicken Price	-0.124	-0.245	-0.050	-0.266
		(-2.14)	(-4.22)	(-0.78)	(-5.66)
	Other Meats Price	-0.154	-0.253	-0.075	0.105
		(-3.85)	(-5.75)	(-1.15)	(-2.84)
Liaoning	Pork Price	-0.395	0.145	-0.272	0.489
		(-3.46)	(1.11)	(-2.09)	(4.08)
	Beef Price	-0.381	-0.759	-0.239	-0.147
		(-3.28)	(-5.13)	(-2.01)	(-1.30)
	Mutton Price	**-0.315** [sh,g,si]	***-0.518*** [sh,g,si]	**-0.519** [sh,g,si]	***-1.246*** [sh,si]
		(-3.28)	***(-4.08)***	**(-6.18)**	***(-11.03)***
	Chicken Price	0.017	0.155	0.150	-0.207
		(0.27)	(2.46)	(2.59)	(-5.66)
	Other Meats Price	-0.244	-0.335	-0.314	-0.102
		(-4.00)	(-4.79)	(-4.42)	(1.65)
Shanghai	Pork Price	1.145	0.297	0.290	0.050
		(5.87)	(1.63)	(1.54)	(0.44)
	Beef Price	-0.293	0.370	0.259	-0.252
		(-2.15)	(3.43)	(2.23)	(-3.55)
	Mutton Price	**-1.135** [g,si]	***-0.623*** [g]	***-1.531*** [si]	***-1.027*** [g,si]
		(-8.47)	**(-5.72)**	**(-17.80)**	**(-18.34)**
	Chicken Price	-0.495	-0.420	-1.027	0.073
		(-3.81)	(-3.65)	(-6.80)	(0.87)
	Other Meats Price	-0.391	-0.616	1.124	0.011
		(-4.89)	(-7.00)	(9.69)	(0.16)
Guangdong	Pork Price	0.646	0.840	0.661	0.140
		(2.00)	(4.59)	(3.44)	(0.89)
	Beef Price	-0.001	0.074	0.336	-0.250
		(-0.01)	(0.74)	(3.00)	(-3.25)
	Mutton Price	**-0.912** [si]	***-1.556*** [si]	***-1.513*** [si]	***-1.277*** [si]
		(-4.73)	**(-17.89)**	**(-18.01)**	**(-15.57)**
	Chicken Price	-0.758	-0.865	-1.403	-0.561
		(-2.79)	(-5.54)	(-8.50)	(-4.68)
	Other Meats Price	-0.009	0.577	1.006	0.773
		(-0.05)	(4.65)	(7.68)	(7.29)
Sichuan	Pork Price	0.134	-0.610	-0.290	-0.427
		(0.33)	(-2.52)	(-0.73)	(-1.60)
	Beef Price	0.418	0.395	0.831	0.058
		(1.55)	(1.89)	(2.56)	(0.33)
	Mutton Price	**-1.237**	***-0.531***	***-1.160***	***-0.621***
		(-4.83)	**(-4.35)**	**(-9.21)**	**(-4.11)**
	Chicken Price	-0.761	-0.707	-0.188	-0.464
		(-2.84)	(-3.52)	(-0.74)	(-2.40)
	Other Meats Price	0.155	0.301	-0.009	0.071
		(0.97)	(3.58)	(-0.05)	(0.55)

Source: 2006, 2009, 2011 and 2015 UHS data.

Table 6D. Marshallian Price Elasticities of Chicken in China

Marshallian Price Elasticities		2006	2009	2011	2015
Overall	**Pork Price**	-0.106	-0.185	0.013	-0.164
		(-2.52)	(-5.61)	(0.32)	(-5.86)
	Beef Price	-0.183	-0.079	-0.081	-0.054
		(-6.10)	(-3.43)	(-2.38)	(-3.00)
	Mutton Price	-0.030	-0.058	-0.008	-0.072
		(-1.03)	(-2.76)	(-0.36)	(-4.24)
	Chicken Price	**-0.660**	***-0.668***	***-0.709***	***-0.688***
		(-24.44)	**(-31.81)**	**(-30.83)**	**(-34.40)**
	Other Meats Price	-0.117	-0.044	-0.235	-0.141
		(-6.16)	(-2.75)	(-9.79)	(-8.81)
Liaoning	**Pork Price**	-0.089	-0.230	0.106	0.097
		(-0.94)	(-2.30)	(1.20)	(0.87)
	Beef Price	-0.240	0.059	0.055	-0.090
		(-2.5)	(0.53)	(0.69)	(-0.85)
	Mutton Price	0.035	0.154	0.107	-0.174
		(0.44)	(1.60)	(1.91)	(-1.64)
	Chicken Price	**-0.814** ^{sh,g,si}	***-0.871*** ^{sh,g,si}	***-0.924*** ^{sh,g,si}	***-0.593*** ^{sh}
		(-15.65)	**(-18.15)**	**(-23.69)**	**(-8.98)**
	Other Meats Price	-0.001	-0.095	-0.358	-0.036
		(-0.02)	(-1.79)	(-7.46)	(-0.62)
Shanghai	**Pork Price**	-0.155	-0.249	-0.172	-0.263
		(-2.54)	(-4.45)	(-2.82)	(-5.60)
	Beef Price	-0.088	0.010	-0.235	0.065
		(-2.05)	-0.3	(-6.18)	-2.17
	Mutton Price	-0.068	-0.076	-0.102	0.024
		(-1.62)	(-2.24)	(-3.64)	-1.04
	Chicken Price	**-0.642** ^{g,si}	***-0.720*** ^{g,si}	***-0.207*** ^{g,si}	***-0.718*** ^{g,si}
		(-15.66)	**(-20.00)**	**(-4.22)**	**(-20.51)**
	Other Meats Price	-0.161	-0.060	-0.758	-0.287
		(-6.44)	(-2.22)	(-20.49)	(-10.25)
Guangdong	**Pork Price**	-0.018	-0.612	-0.326	-0.239
		(-0.19)	(-10.20)	(-5.17)	(-5.69)
	Beef Price	-0.171	-0.142	-0.262	-0.113
		(-3.05)	(-4.30)	(-7.08)	(-5.14)
	Mutton Price	-0.059	-0.059	-0.110	-0.057
		(-1.02)	(-2.03)	(-4.07)	(-2.38)
	Chicken Price	**-0.638**	***-0.192*** ^{si}	***-0.167*** ^{si}	***-0.562***
		(-7.78)	**(-3.69)**	**(-3.09)**	**(-16.53)**
	Other Meats Price	-0.203	-0.381	-0.508	-0.183
		(-3.90)	(-9.29)	(-11.81)	(-6.54)
Sichuan	**Pork Price**	-0.308	-0.261	-1.005	-0.443
		(-2.66)	(-3.73)	(-9.66)	(-5.34)
	Beef Price	-0.190	-0.232	0.233	-0.044
		(-2.47)	(-3.87)	-2.74	(-0.81)
	Mutton Price	-0.049	-0.054	-0.018	-0.065
		(-0.67)	(-1.54)	(-0.55)	(-1.35)
	Chicken Price	**-0.354**	**-0.425**	**-0.263**	**-0.528**
		(-4.66)	**(-7.33)**	**(-3.93)**	**(-9.10)**
	Other Meats Price	-0.100	-0.003	0.012	-0.090
		(-2.17)	(-0.13)	-0.27	(-2.25)

Source: 2006, 2009, 2011 and 2015 UHS data.

Table 6E. Marshallian Price Elasticities of Other Meats in China

Marshallian Price Elasticities		2006	2009	2011	2015
Overall	Pork Price	-0.236 (-5.76)	-0.207 (-6.27)	-0.294 (-7.17)	-0.392 (-15.68)
	Beef Price	-0.168 (-5.60)	-0.121 (-5.04)	-0.002 (-0.06)	0.054 (3.18)
	Mutton Price	-0.014 (-0.48)	-0.030 (-1.43)	-0.004 (-0.18)	0.025 (1.67)
	Chicken Price	-0.046 (-1.70)	-0.014 (-0.64)	-0.128 (-5.57)	-0.065 (-3.61)
	Other Meats Price	**-0.403** **(-21.21)**	***-0.579*** **(-36.19)**	***-0.519*** **(-21.63)**	***-0.633*** **(-48.69)**
Liaoning	Pork Price	-0.250 (-2.72)	-0.193 (-1.75)	-0.200 (-2.53)	-0.121 (-1.55)
	Beef Price	-0.118 (-1.26)	-0.203 (-1.65)	-0.020 (-0.27)	0.043 (0.59)
	Mutton Price	-0.104 (-1.33)	-0.145 (-1.37)	-0.081 (-1.59)	-0.019 (0.26)
	Chicken Price	-0.010 (-0.20)	-0.061 (-1.15)	-0.166 (-4.61)	-0.023 (-0.51)
	Other Meats Price	**-0.536** [sh,si] **(-10.94)**	***-0.377*** [sh,g,si] **(-6.39)**	***-0.490*** [sh,g,si] **(-11.40)**	***-0.777*** [sh,g] **(-19.43)**
Shanghai	Pork Price	-0.141 (-2.47)	-0.156 (-3.39)	-0.672 (-10.18)	-0.331 (-7.70)
	Beef Price	-0.252 (-6.30)	-0.179 (-6.63)	0.037 (0.90)	0.036 (1.33)
	Mutton Price	-0.026 (-0.65)	-0.044 (-1.63)	0.078 (2.60)	0.012 (0.57)
	Chicken Price	-0.054 (-1.42)	0.000 (-0.00)	-0.517 (-9.75)	-0.095 (-2.97)
	Other Meats Price	**-0.340** [g,si] **(-14.17)**	**-0.530** [g,si] **(-24.09)**	***-0.174*** [si] **(-4.24)**	***-0.529*** [g,si] **(-20.35)**
Guangdong	Pork Price	-0.441 (-4.16)	-0.203 (-3.08)	-0.457 (-5.86)	-0.681 (-15.13)
	Beef Price	0.035 (0.57)	0.014 (0.39)	0.038 (0.86)	0.096 (4.17)
	Mutton Price	0.001 (0.02)	0.035 (1.13)	0.068 (2.00)	0.064 (2.56)
	Chicken Price	-0.174 (-1.96)	-0.359 (-6.41)	-0.438 (-6.64)	-0.132 (-3.67)
	Other Meats Price	**-0.326** [si] **(-5.62)**	**-0.495** [si] **(-11.00)**	***-0.178*** [si] **(-3.36)**	***-0.420*** [si] **(-14.48)**
Sichuan	Pork Price	-0.206 (-1.89)	-0.253 (3.33)	-0.204 (-1.96)	-0.254 (-4.10)
	Beef Price	-0.002 (-0.03)	0.123 (1.86)	-0.056 (-0.66)	0.009 (0.22)
	Mutton Price	0.010 (0.14)	0.015 (0.39)	-0.002 (-0.06)	0.009 (0.24)
	Chicken Price	-0.055 (-0.77)	-0.010 (-0.16)	0.018 (0.27)	-0.031 (-0.67)
	Other Meats Price	**-0.669** **(-15.20)**	***-0.915*** **(35.19)**	***-0.694*** **(-15.77)**	***-0.763*** **(-27.25)**

Source: 2006, 2009, 2011 and 2015 UHS data.

Table 7A. Marshallian Price Elasticities of Pork in Liaoning by Household Income

Marshallian Price Elasticities		2006	2009	2011	2015
Low Income	Pork Price	**-0.934**^{h}	***-1.022***^{m,h}	**-0.960**^{m,h}	***-1.074***^{m,h}
		(-13.34)	**(-16.75)**	**(-16.00)**	**(-21.06)**
	Beef Price	0.230	0.154	0.055	-0.025
		(3.07)	(2.30)	(0.98)	(-0.53)
	Mutton Price	-0.072	0.071	-0.036	0.029
		(-1.22)	(1.22)	(-0.90)	(0.53)
	Chicken Price	-0.003	-0.033	0.021	0.012
		(-0.08)	(-1.18)	(0.78)	(0.39)
	Other Meats Price	-0.044	-0.032	-0.033	-0.009
		(-1.13)	(-1.00)	(-1.00)	(-0.36)
Middle Income	Pork Price	**-0.993**^{h}	***-0.937***^{h}	***-1.030***^{h}	***-1.077***^{h}
		(-13.99)	**(-11.02)**	**(-14.93)**	**(-17.95)**
	Beef Price	0.198	0.100	0.019	0.030
		(2.79)	(1.09)	(0.30)	(0.52)
	Mutton Price	-0.009	0.026	-0.030	0.117
		(-0.15)	(0.33)	(-0.73)	(1.98)
	Chicken Price	0.019	-0.010	0.066	-0.012
		(0.48)	(-0.26)	(2.20)	(-0.36)
	Other Meats Price	-0.067	-0.023	-0.039	-0.058
		(-1.81)	(-0.53)	(-1.05)	(-1.81)
High Income	Pork Price	**-1.036**	***-1.057***	***-0.865***	***-0.931***
		(-14.00)	**(-12.89)**	**(-12.72)**	**(-15.02)**
	Beef Price	0.179	0.279	0.003	0.012
		(2.42)	(2.97)	(0.05)	(0.20)
	Mutton Price	-0.046	0.027	-0.009	0.058
		(-0.74)	(0.33)	(-0.20)	(1.09)
	Chicken Price	0.012	-0.040	-0.019	-0.018
		(0.28)	(-0.93)	(-0.61)	(-0.49)
	Other Meats Price	-0.074	-0.105	-0.132	-0.120
		(-1.85)	(-2.28)	(-3.47)	(-3.53)

Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "m" means the elasticity is significantly different between low and middle income household; (m=middle household income group, h=high household income group)

Table 7B. Marshallian Price Elasticities of Beef in Liaoning by Household Income

Marshallian Price Elasticities		2006	2009	2011	2015
Low Income	Pork Price	0.586 (2.97)	0.262 (1.88)	0.161 (0.87)	-0.224 (-1.00)
	Beef Price	**-1.282** **(-6.10)**	***-1.084***^{m,h} **(-6.56)**	***-1.403***^{m,h} **(-8.16)**	***-0.927***^{m,h} **(-4.50)**
	Mutton Price	-0.262 (-1.58)	-0.341 (-2.60)	-0.005 (-0.04)	0.072 (0.30)
	Chicken Price	-0.138 (-1.31)	-0.013 (-0.20)	-0.009 (-0.11)	-0.018 (-0.13)
	Other Meats Price	-0.155 (-1.44)	-0.145 (-2.01)	0.146 (1.46)	-0.012 (-0.11)
Middle Income	Pork Price	0.450 (2.46)	0.049 (0.27)	0.005 (0.03)	0.037 (0.24)
	Beef Price	**-1.306** **(-7.14)**	***-0.958***^{h} **(-4.96)**	***-0.931***^{h} **(-5.89)**	***-1.003***^{h} **(-6.97)**
	Mutton Price	-0.203 (-1.28)	-0.266 (-1.62)	-0.125 (-1.20)	-0.068 (-0.46)
	Chicken Price	-0.218 (-2.14)	-0.061 (-0.74)	-0.037 (-0.49)	-0.114 (-1.37)
	Other Meats Price	-0.052 (-0.55)	-0.067 (-0.74)	-0.056 (-0.61)	-0.016 (-0.20)
High Income	Pork Price	0.485 (2.72)	0.489 (3.20)	-0.023 (-0.15)	-0.046 (-0.38)
	Beef Price	**-1.150** **(-6.50)**	***-1.020*** **(05.80)**	***-0.813*** **(-5.81)**	***-1.097*** **(-8.70)**
	Mutton Price	-0.212 (-1.43)	-0.385 (02.50)	-0.111 (-1.06)	-0.038 (-0.37)
	Chicken Price	-0.211 (-2.05)	0.015 (0.19)	0.106 (1.47)	-0.105 (-1.46)
	Other Meats Price	-0.089 (-0.93)	-0.371 (-4.26)	-0.251 (-2.85)	0.041 (0.61)

Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "m" means the elasticity is significantly different between low and middle income household; (m=middle household income group, h=high household income group)

Table 7C. Marshallian Price Elasticities of Mutton in Liaoning by Household Income

Marshallian Price Elasticities		2006	2009	2011	2015
Low Income	Pork Price	-0.681	0.218	-0.503	0.253
		(-3.08)	(1.26)	(-2.16)	(0.93)
	Beef Price	-0.460	-0.702	-0.019	0.102
		(-1.95)	(-3.68)	(-0.09)	(0.41)
	Mutton Price	**-0.164**	***-0.601***	***-0.694***	***-1.662***
		(-0.87)	**(-3.69)**	**(-4.48)**	**(-5.67)**
	Chicken Price	0.173	0.135	0.337	0.044
		(1.48)	(1.71)	(3.21)	(0.26)
	Other Meats Price	-0.144	-0.326	-0.298	0.038
		(-1.18)	(-3.62)	(-2.37)	(0.29)
Middle Income	Pork Price	-0.269	-0.104	-0.315	0.678
		(-1.39)	(-0.47)	(-1.32)	(3.32)
	Beef Price	-0.316	-0.551	-0.274	-0.105
		(-1.64)	(-2.31)	(-1.26)	(-0.55)
	Mutton Price	**-0.377**	**-0.589**	**-0.510**	***-1.258***
		(-2.24)	**(-2.92)**	**(-3.57)**	**(-6.35)**
	Chicken Price	-0.118	0.088	0.102	-0.307
		(-1.09)	(0.87)	(0.98)	(-2.74)
	Other Meats Price	-0.219	-0.214	-0.147	-0.152
		(-2.19)	(-1.91)	(-1.17)	(-1.43)
High Income	Pork Price	-0.375	-0.075	-0.145	0.229
		(-2.11)	(-0.38)	(-0.70)	(1.33)
	Beef Price	-0.322	-0.726	-0.262	-0.070
		(-1.82)	(-3.14)	(-1.41)	(-0.42)
	Mutton Price	**-0.282**	**-0.336**	**-0.308**	**-1.008**
		(-1.89)	**(-1.67)**	**(-2.18)**	**(-6.95)**
	Chicken Price	-0.040	0.116	-0.013	-0.194
		(-0.39)	(1.10)	(-0.14)	(-1.90)
	Other Meats Price	-0.298	-0.320	-0.464	-0.127
		(-3.10)	(-2.83)	(-3.93)	(-1.35)

Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "m" means the elasticity is significantly different between low and middle income household; (m=middle household income group, h=high household income group)

Table 7D. Marshallian Price Elasticities of Chicken in Liaoning by Household Income

Marshallian Price Elasticities		2006	2009	2011	2015
Low Income	Pork Price	-0.184	-0.198	0.071	0.411
		(-1.13)	(-1.52)	(0.49)	(1.69)
	Beef Price	-0.188	0.025	-0.003	0.019
		(-1.07)	(0.17)	(-0.02)	(0.09)
	Mutton Price	0.159	0.124	0.188	0.067
		1.15	(1.02)	(1.94)	(0.26)
	Chicken Price	**-1.029**	**-0.902**^{m}	***-0.998*** ^{m,h}	**-1.036** ^{m,h}
		(-11.83)	**(-15.29)**	**(-15.35)**	**(07.00)**
	Other Meats Price	0.099	-0.028	-0.301	-0.077
		(1.10)	(-0.42)	(-3.81)	(00.66)
Middle Income	Pork Price	-0.028	-0.126	0.379	0.003
		(-0.17)	(-0.77)	(2.33)	(0.02)
	Beef Price	-0.291	-0.052	-0.028	-0.146
		(-1.73)	(-0.30)	(-0.19)	(-0.87)
	Mutton Price	-0.094	0.102	0.078	-0.295
		(-0.64)	(0.68)	(0.80)	(-1.70)
	Chicken Price	**-0.727**	***-0.832***	***-1.022***^{h}	***-0.519***
		(-7.73)	**(-11.09)**	**(-14.39)**	**(-5.24)**
	Other Meats Price	0.035	-0.118	-0.368	0.118
		(0.40)	(-1.42)	(-4.23)	(1.27)
High Income	Pork Price	-0.025	-0.225	-0.135	-0.030
		(-0.16)	(-1.48)	(-0.91)	(-0.18)
	Beef Price	-0.305	0.069	0.175	-0.164
		(-1.91)	(0.39)	(1.33)	(-1.01)
	Mutton Price	-0.023	0.142	-0.003	-0.187
		(-0.17)	(0.93)	(-0.03)	(-1.33)
	Chicken Price	**-0.638**	***-0.767***	***-0.689***	***-0.264***
		(-6.86)	**(-9.59)**	**(-9.99)**	**(-2.59)**
	Other Meats Price	-0.147	-0.256	-0.435	-0.184
		(-1.71)	(-2.98)	(-5.24)	(-2.02)

Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "m" means the elasticity is significantly different between low and middle income household; (m=middle household income group, h=high household income group)

Table 7E. Marshallian Price Elasticities of Other Meats in Liaoning by Household Income

Marshallian Price Elasticities		2006	2009	2011	2015
Low Income	Pork Price	-0.341	-0.181	-0.137	0.186
		(-1.88)	(-1.26)	(-0.94)	(1.06)
	Beef Price	-0.158	-0.118	0.121	0.025
		(-0.81)	(-0.75)	(0.89)	(0.16)
	Mutton Price	-0.081	-0.148	-0.084	0.042
		(-0.53)	(-1.10)	(-0.87)	(0.23)
	Chicken Price	0.076	-0.026	-0.172	-0.045
		(0.78)	(-0.39)	(-2.65)	(-0.42)
	Other Meats Price	**-0.632**^{m,h}	**-0.563** ^{m,h}	**-0.727** ^{m,h}	**-0.924** ^{m,h}
		(-6.32)	**(-7.51)**	**(-9.20)**	**(-10.87)**
Middle Income	Pork Price	-0.231	-0.089	-0.011	-0.104
		(-1.50)	(-0.47)	(-0.08)	(-0.79)
	Beef Price	0.013	0.002	0.003	0.024
		(0.08)	(0.01)	(0.02)	(0.19)
	Mutton Price	-0.080	-0.068	-0.027	-0.045
		(-0.60)	(-0.39)	(-0.33)	(-0.35)
	Chicken Price	0.035	-0.060	-0.166	0.045
		(0.41)	(-0.69)	(-2.77)	(0.63)
	Other Meats Price	**-0.677**^{h}	**-0.688** ^{h}	**-0.637** ^{h}	**-0.810**
		(-8.46)	**(-7.09)**	**(-8.61)**	**(-11.74)**
High Income	Pork Price	-0.064	-0.186	-0.177	-0.202
		(-0.46)	(-1.13)	(-1.43)	(-1.84)
	Beef Price	0.000	-0.273	-0.120	0.084
		(0.00)	(-1.44)	(-1.08)	(0.79)
	Mutton Price	-0.093	-0.113	-0.109	-0.026
		(-0.81)	(-0.68)	(-1.31)	(-0.28)
	Chicken Price	-0.032	-0.114	-0.146	-0.071
		(-0.40)	(-1.33)	(-2.52)	(-1.09)
	Other Meats Price	**-0.435**	***-0.083***	***-0.253***	***-0.642***
		(-7.13)	**(-0.87)**	**(-3.56)**	**(-10.70)**

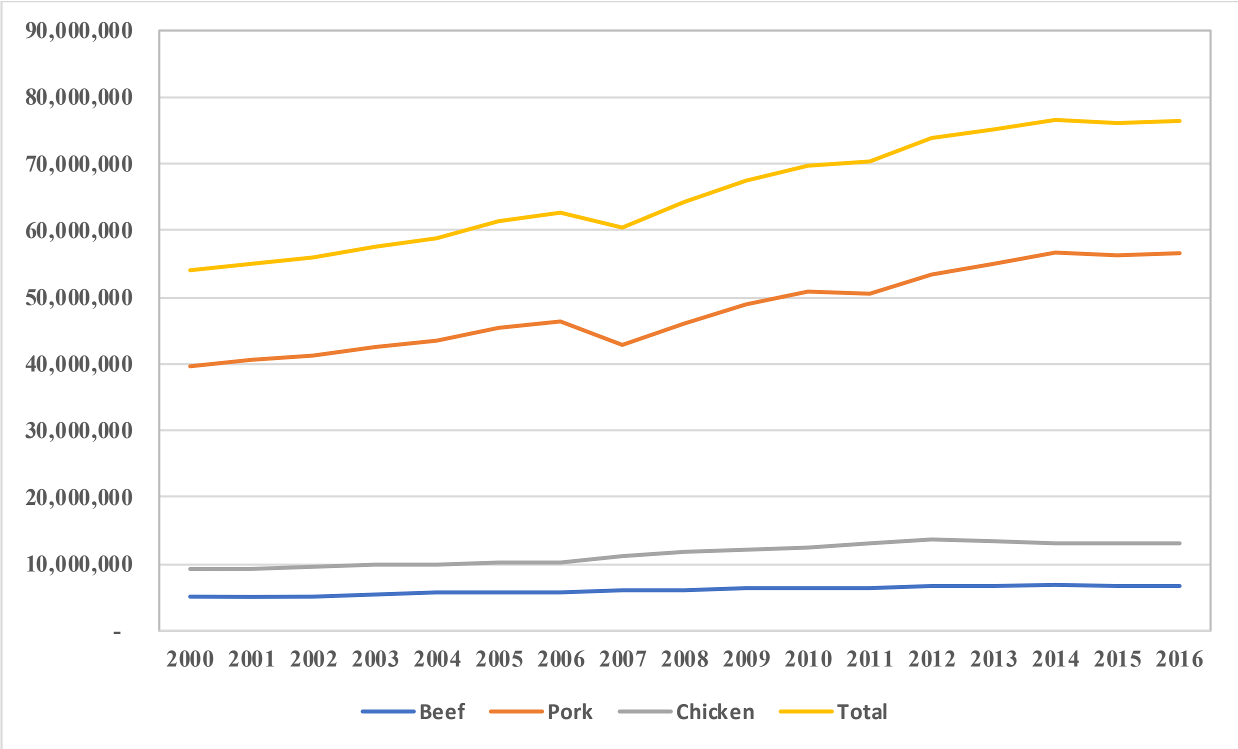
Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The numbers in brackets under the elasticities are the corresponding t-statistics. The number in Italic means it is significantly different from the number in previous year. The superscript means it is significantly difference from province, eg: subscript "m" means the elasticity is significantly different between low and middle income household; (m=middle household income group, h=high household income group)

Table 8. Hicksian Price Elasticities of Meats in China

Hicksian Price Elasticities		2006	2009	2011	2015
Pork Share	Pork Price	**-0.393 (-19.65)**	**-0.330 (-18.33)**	**-0.340 (-16.19)**	**-0.264 (-22.00)**
	Beef Price	0.138 (9.20)	0.057 (4.38)	0.095 (5.28)	0.052 (6.50)
	Mutton Price	0.044 (3.14)	0.051 (4.64)	0.023 (2.09)	0.050 (7.14)
	Chicken Price	0.123 (9.46)	0.093 (7.75)	0.137 (11.42)	0.096 (12.00)
	Other Meats Price	0.088 (9.78)	0.128 (14.22)	0.085 (7.08)	0.066 (11.00)
Beef Share	Pork Price	0.861 (12.48)	0.312 (5.29)	0.524 (7.49)	0.379 (8.24)
	Beef Price	**-0.659 (-9.00)**	**-0.574 (-6.52)**	**-0.786 (-13.32)**	**-0.743 (-25.62)**
	Mutton Price	-0.023 (-0.47)	0.040 (1.08)	0.034 (0.89)	-0.045 (-1.67)
	Chicken Price	-0.145 (-3.22)	0.021 (0.54)	0.020 (0.50)	0.048 (1.50)
	Other Meats Price	-0.233 (-7.28)	-0.099 (-3.30)	0.207 (5.05)	0.361 (15.04)
Mutton Share	Pork Price	0.597 (6.78)	0.670 (7.61)	0.362 (3.23)	0.848 (12.66)
	Beef Price	-0.051 (-0.78)	0.096 (1.52)	0.099 (1.05)	-0.102 (-2.32)
	Mutton Price	**-0.696 (-11.05)**	**-0.729 (-13.02)**	**-0.745 (-12.42)**	**-0.997 (-25.56)**
	Chicken Price	0.046 (0.79)	-0.075 (-1.32)	0.101 (1.60)	-0.119 (-2.59)
	Other Meats Price	0.104 (2.60)	0.037 (0.84)	0.183 (2.77)	0.371 (10.31)
Chicken Share	Pork Price	0.474 (11.56)	0.320 (10.00)	0.543 (13.24)	0.467 (16.68)
	Beef Price	-0.090 (-3.00)	0.013 (0.57)	0.015 (0.44)	0.032 (1.78)
	Mutton Price	0.013 (0.45)	-0.019 (-0.90)	0.025 (1.14)	-0.035 (-2.06)
	Chicken Price	**-0.509 (-18.85)**	**-0.521 (-24.81)**	**-0.575 (-25.00)**	**-0.559 (-27.95)**
	Other Meats Price	0.112 (5.89)	0.207 (12.94)	-0.007 (-0.29)	0.095 (6.33)
Other Meats Share	Pork Price	0.223 (5.44)	0.257 (7.79)	0.198 (4.83)	0.177 (7.08)
	Beef Price	-0.094 (-3.13)	-0.036 (-1.50)	0.087 (2.49)	0.132 (7.76)
	Mutton Price	0.020 (0.69)	0.006 (0.29)	0.027 (1.23)	0.059 (3.93)
	Chicken Price	0.074 (2.74)	0.121 (5.50)	-0.004 (-0.17)	0.052 (3.06)
	Other Meats Price	**-0.222 (-11.68)**	**-0.348 (-21.75)**	**-0.308 (-12.83)**	**-0.420 (-30.00)**

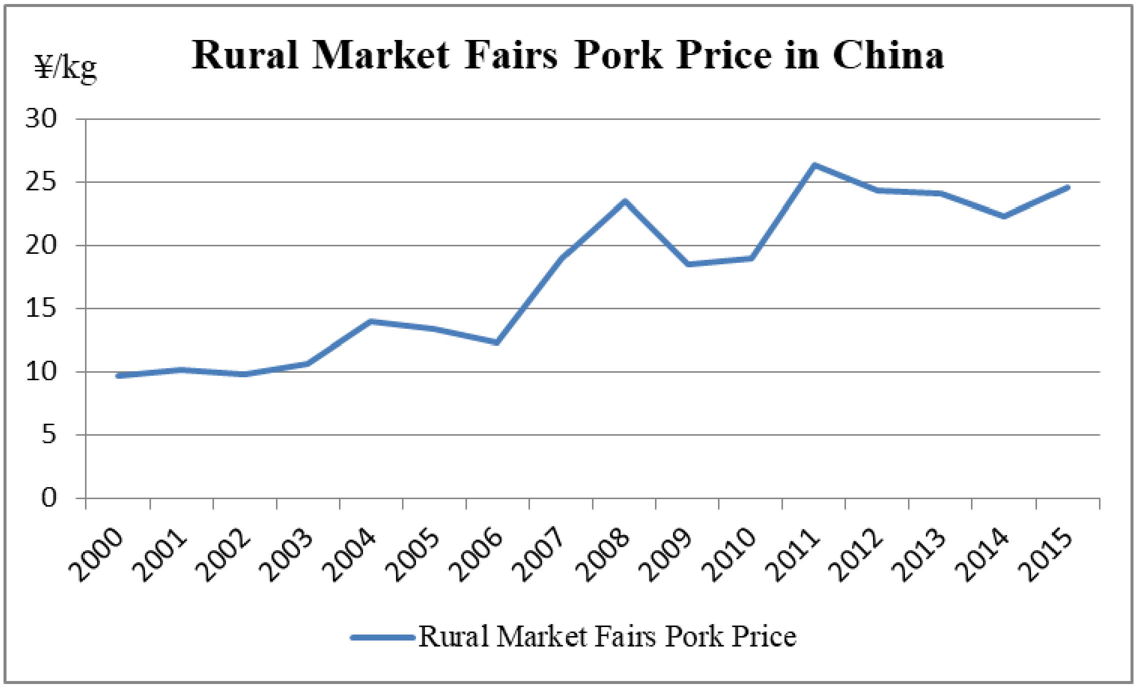
Source: 2006, 2009, 2011 and 2015 UHS data.
Note: The numbers in brackets under the elasticities are the corresponding t-statistics.

(Metric tons)



Source: FAS/USDA

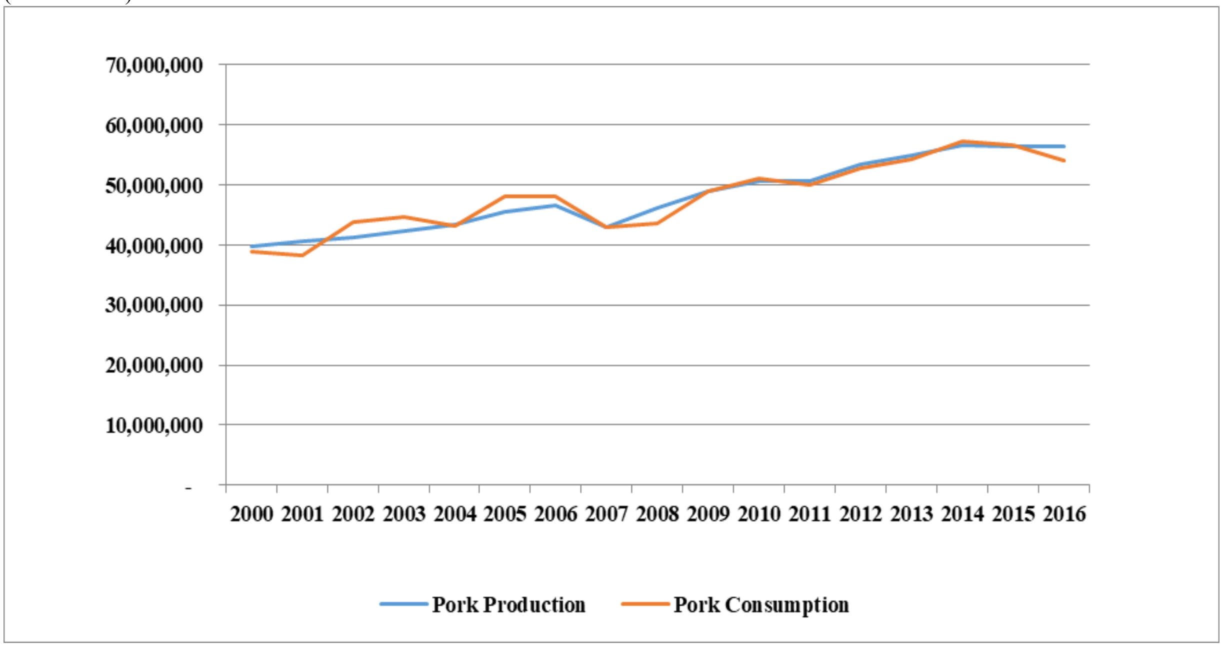
Figure 1. Meat production in China, 2000–2016



Source: *China Yearbook of Agricultural Price Survey.*

Figure 2. Rural Market Fairs Pork Prices in China, 2000–2015

(Metric tons)



Source: USDA-FAS

Figure 3. Pork Production and Consumption in China, 2000–2016

Appendix

Table A1 AIDS Model Parameter Estimates (four provinces overall)

Parameters		2006	2009	2011	2015
Pork Share	γ_ln(Pork Price)	0.042 (4.00)	0.092 (10.48)	0.074 (6.70)	0.116 (16.96)
	γ_ln(Beef Price)	0.027 (3.48)	-0.018 (-2.95)	-0.0002 (-0.02)	-0.023 (-5.08)
	γ_ln(Mutton Price)	0.002 (0.24)	0.006 (0.99)	-0.005 (-0.93)	0.006 (1.40)
	γ_ln(Chicken Price)	-0.009 (-1.30)	-0.025 (-4.34)	0.003 (0.47)	-0.017 (-3.52)
	γ_ln(Other Meats Price)	-0.062 (-13.04)	-0.054 (-12.38)	-0.071 (-11.04)	-0.082 (-21.50)
	η_lnY	-0.008 (-3.40)	-0.016 (-7.73)	-0.006 (-2.89)	-0.046 (-28.51)
	α	0.364 (11.62)	0.270 (10.65)	0.407 (13.32)	-0.036 (-2.11)
Beef Share	γ_ln(Pork Price)	0.027 (4.57)	-0.018 (-3.49)	-0.0002 (-0.03)	-0.023 (-6.52)
	γ_ln(Beef Price)	0.041 (9.37)	0.060 (15.76)	0.012 (2.23)	0.018 (7.78)
	γ_ln(Mutton Price)	-0.004 (-0.93)	0.002 (0.45)	0.001 (0.21)	-0.004 (-2.02)
	γ_ln(Chicken Price)	-0.022 (-5.72)	-0.010 (-2.90)	-0.010 (-2.70)	-0.003 (-1.03)
	γ_ln(Other Meats Price)	-0.042 (-15.62)	-0.033 (-12.38)	-0.003 (-0.73)	0.012 (6.02)
	η_lnY	0.014 (9.96)	0.016 (12.79)	0.010 (7.87)	0.021 (19.06)
	α	0.229 (12.96)	0.232 (15.15)	0.156 (8.47)	0.300 (26.71)
Mutton Share	γ_ln(Pork Price)	0.002 (0.52)	0.006 (1.69)	-0.005 (-1.49)	0.006 (2.63)
	γ_ln(Beef Price)	-0.004 (-1.52)	0.002 (0.65)	0.001 (0.24)	-0.004 (-2.94)
	γ_ln(Mutton Price)	0.011 (4.61)	0.009 (4.46)	0.008 (3.84)	0.0003 (0.22)
	γ_ln(Chicken Price)	-0.002 (-0.98)	-0.008 (-3.59)	-0.001 (-0.40)	-0.007 (-4.34)
	γ_ln(Other Meats Price)	-0.007 (-4.46)	-0.009 (-5.30)	-0.002 (-0.93)	0.006 (4.43)
	η_lnY	0.009 (11.53)	0.007 (9.46)	0.005 (7.12)	0.009 (9.29)
	α	0.146 (14.04)	0.105 (11.07)	0.084 (8.28)	0.110 (11.72)

Table A1 Continued

AIDS Model Parameter Estimates (four provinces overall)

Chicken Share	**γ_ln(Pork Price)**	-0.009 (-1.57)	-0.025 (-5.36)	0.003 (0.55)	-0.017 (-5.22)
	γ_ln(Beef Price)	-0.022 (-5.24)	-0.010 (-3.02)	-0.010 (-2.24)	-0.003 (-1.19)
	γ_ln(Mutton Price)	-0.002 (-0.55)	-0.008 (-2.61)	-0.001 (-0.29)	-0.007 (-3.43)
	γ_ln(Chicken Price)	0.051 (13.68)	0.048 (15.99)	0.039 (12.74)	0.039 (17.33)
	γ_ln(Other Meats Price)	-0.017 (-6.80)	-0.006 (-2.53)	-0.031 (-9.77)	-0.013 (-7.21)
	η_lnY	0.013 (10.01)	0.005 (4.62)	0.003 (2.52)	0.014 (16.05)
	α	0.371 (21.87)	0.273 (20.36)	0.286 (19.22)	0.363 (40.79)
Other Meats Share	**γ_ln(Pork Price)**	-0.062 (-7.23)	-0.054 (-6.73)	-0.071 (-7.74)	-0.082 (-15.74)
	γ_ln(Beef Price)	-0.042 (-6.63)	-0.033 (-5.68)	-0.003 (-0.37)	0.012 (3.46)
	γ_ln(Mutton Price)	-0.007 (-1.16)	-0.009 (-1.69)	-0.002 (-0.40)	0.006 (1.74)
	γ_ln(Chicken Price)	-0.017 (-3.15)	-0.006 (-1.11)	-0.031 (-5.88)	-0.013 (-3.60)
	γ_ln(Other Meats Price)	0.128 (32.66)	0.101 (25.43)	0.106 (19.85)	0.078 (26.92)
	η_lnY	-0.028 (-13.99)	-0.012 (-6.49)	-0.012 (-6.54)	0.002 (1.02)
	α	-0.110 (-4.29)	0.120 (5.15)	0.066 (2.59)	0.263 (12.82)

Source: 2006, 2009, 2011 and 2015 UHS data.

Note: The numbers in brackets under the elasticities are the corresponding z-statistics.

CHAPTER 4. ESTIMATION OF ECONOMIC IMPACTS OF ADOPTING TRANSGENIC APPROACHES FOR MANAGING SOYBEAN SUDDEN DEATH SYNDROME IN THE UNITED STATES

Abstract

We use a crop sector model and World Agricultural Supply and Demand Estimates data to estimate the total supply and prices of Sudden Death Syndrome-resistant transgenic soybeans. Our findings indicate that if the United States had adopted Sudden Death Syndrome-resistant transgenic soybeans in the past, soybean market equilibrium total supply (demand) would have increased by 0.1%–0.5% from 2000–2017, soybean prices would have decreased by about 0.1%, soybean crush would have decreased by 0%–0.2%, exports would have increased by 0.1%–0.4%, and stocks would have increased by 0.1%–3.8%. Adoption of Sudden Death Syndrome-resistant transgenic soybeans will bring larger benefits to producers than consumers, in general. Producer benefits would have peaked in the years with the largest outbreaks.

Keywords: Sudden Death Syndrome, transgenic soybean, economic benefits, consumer/producer surplus

Introduction

Soybeans are one of the oldest crops, having been cultivated in China as early as 3000 BC. Soybeans were introduced to North America at the beginning of the nineteenth century; and, in the early twentieth century, Americans began recognizing soybean's value as a source of both food and oil. Over time, soybeans have become the second largest cash crop, following only corn in acreage.

Soybeans can suffer from plant diseases, which can lead to a reduction in output and cause economic losses. Sudden death syndrome (SDS) is a major soybean disease that causes economic and production losses for farmers in the United States every year. Scherm and Yang (1999) determined that weather conditions are most conducive to SDS in the central United States; and, Wrather and Koenning (2006) showed that the northern United States suffers more severe SDS than the southern United States. They also estimated that in 2005, SDS yield suppression in the United States totaled $118.90 million. Koenning and Wrather (2010) estimated that SDS yield losses in the United States increased from 27.32 million bushels in 2006 to 34.473 million bushels in 2009. Navi and Yang (2016) estimated total SDS economic losses at $3.06 billion from 1988 to 2010, with losses increasing from $15.70 million in 1988 to $669.20 million in 2010. Wang et al. (2015) estimated that in 2010, SDS caused yield losses of 70 million bushels in the United States.

To gain a rough view of SDS's total impact on soybean economic production value, Figure 1 shows the total value of U.S. soybean production and the value of SDS impacted soybeans. While the value of soybean production impacted by SDS is very low compared to total soybean production values, the losses still add up to millions of dollars in lost revenue. Figure 2 shows the percentage of U.S. soybeans impacted by SDS every year, which has never been more than 3%.

The percentage of U.S. soybeans affected by SDS varies year to year and is influenced by weather and crop planting patterns.

While the proportion of U.S. soybeans impacted by SDS is small, the economic loss reaches into the millions of dollars per year, so SDS is considered a severe disease. Wrather and Koenning (2006) reveal that SDS is among the top diseases that suppress soybean yield. Wrather and Koenning (2006) also reveal that SDS causes more economic losses in the Midwest, especially Illinois and Indiana.

Genetically modified soybeans have undergone long testing procedures before being allowed for commercial use. Kalaitzandonakes et al. (2015) find that countries have differing regulatory approval procedures for new biotech crops. Jaffe (2005) estimated that, in the mid-2000s, it took an average of 13.6 months for biotech crop approval in United States, and much longer in the European Union. Regulatory requirements vary across countries, and any new type of genetically modified soybean, such as a transgenic soybean, must be approved both in the exporting and importing countries.

There have been a few studies that research the economic changes that transgenic crops bring to individual producers, seed companies, and the economy as a whole. Konduru, Kruse, and Kalaitzandonakes (2008) analyze the global economic impacts of Roundup Ready (RR) soybeans, as well as the distribution of economic benefits. They find a $31 billion benefit to all parties, including consumers and producers all over the world, as well as the supply chain of the soybean complex, and find large aggregate economic impacts from adopting RR soybean. They also find that early adopters benefited most from RR soybeans, while producers using competitive oil seeds, which did not benefit from parallel technology, experienced economic losses; and, that consumers benefited almost as much as producers through the use of soybean oils and meals. Bayer, Norton, and Falck-Zepeda (2010) analyze the costs of regulations for four genetically modified products in the Philippines—Bt eggplant, Bt rice, ring-spot-virus-resistant papaya, and virus-resistant tomatoes. They find that direct regulatory costs are significant, but lower than the technology development costs. They also find direct regulatory costs were reduced in countries as they gained more experience with genetically modified products. Kalaitzandonakes, Zahringer, and Kruse (2015) study the potential economic influences of new transgenic soybean regulatory approval delay. They find that if new transgenic soybeans are approved and commercialized in a timely fashion, the economic benefits from their adoption can be as large as $40 billion for the studied 10-year period. They also find that when new traits for transgenic soybeans are delayed in reaching the market, the distribution of the economic benefits changes. However, these studies do not take into account the influence of transgenic soybean adoption on producers' cost structures. The effects of transgenic soybean adoption can be multi-dimensional, thus it may affect yield and cost structure at the same time.

In this study, we estimate a soybean crop sector model to forecast the U.S. soybean market, and then use the change in producer and consumer surplus to analyze the real impacts on producers' farms, and the U.S. economy as a whole, that the introduction of transgenic soybeans brings. Our paper has two key features: (a) we incorporate the influences of SDS-resistant soybean varieties on yields and production costs in our model to make it more complete for explaining the economic effects of SDS-resistant soybean adoption; and, (b) we estimate the welfare effects that the introduction of SDS-resistant soybeans will bring to the U.S. economy. This work is part of a larger grant project funded by USDA-NIFA, "Transgenic Approaches in Managing Sudden Death Syndrome in Soybean." Some of the assumptions made within the modeling structure are driven by information obtained from researchers involved in other facets of the grant, including prospective adoption rates, yield changes, and production cost shifts.

The rest of the paper is arranged as follows. The background and farm-level impacts section introduces the background of the method we use before setting up the SDS-resistant soybean adoption counterfactual scenario. The methodology section introduces the methodology. The scenario development section and the soybean crop sector model section set up the counterfactual scenario and soybean crop-sector models, respectively. The data and results section presents empirical results, followed by my conclusion section.

Background and Farm-Level Impacts

Many previous studies examine the cost/benefit analysis of biotech crops. Many of these studies are conducted in the form of field trials—for example, Carpenter and Gianessi (2003). By assessing the economic benefits and costs of conventional crops, and then comparing them with genetically modified crops in a field experiment, we can partly estimate the differences in their performances. However, this approach can be biased because biotech crops may have multiple effects, and some potential effects might be overlooked.

Other studies compare the performances of biotech crop adopters and that of non-adopters; however, differences in other factors (e.g., land productivity) may cause systematic biases. Some studies compare the performances of biotech crops against conventional crops on partial-adopters' farms (Marra 2001); however, unobserved factors influencing partial adoption can still bias estimations.

In reality, biotech crop adoption may have compound influences on adopters' performances. Biotech crops can change a farmer's productivity by altering per-acre crop yield, which in turn may change crop prices, thus further changing the farmer's total benefits. Concurrently, biotech crop adoption might also change producers' cost structures. Biotech crop seeds may be more expensive than the conventional varieties, which can increase farmer's seed expenditure; however, farmers may use cheaper and more effective ways to confront crop diseases and control weeds, providing savings on chemicals and crop insurance expenditures from production losses. Adoption may also change fertilizer costs, harvest costs, and land costs. Thus, I take into account the compound effects of adopting a new variety of genetically modified crop in my study.

Alston et al. (2014) studied the economic impacts of the introduction of the RR soybean, which is genetically modified to be glyphosate-resistant, thus allowing farmers to adopt over-the-top glyphosate use to control weeds and lower production costs. To study farmers' benefits of RR soybean adoption, they establish a counterfactual scenario (a scenario in which the RR soybean had not been adopted). In our research, we use the same approach as Alston et al. (2014) to establish a counterfactual scenario of the adoption of SDS resistant soybeans and apply that scenario within a crop sector model.

Methodology

Alston et al. (2014) create a decision model to establish RR soybean adoption and non-adoption scenarios. They also set up a global partial equilibrium model to estimate the global market demand and supply of soybean for meals and oil crush or oilseeds, and competing crops in other major crop-producing countries, major crop-importing countries, and other major countries in the international market. Following Alston et al. (1995), they use a formula for the change in producer and consumer surplus to estimate the welfare effects of biotech crop adoption on the whole economy. Many other studies use a similar approach, when analyzing biotech crops. Konduru, Kruse, and Kalaitzandonakes (2008) use the same model to study the economic impacts of RR soybean adoption on the global market. They also incorporate a welfare distribution analysis in their study. Bayer, Norton, and Falck-Zepeda (2010) use similar approaches to study the costs of regulations on transgenic crop adoption in the Philippines. Kalaitzandonakes, Zahringer and Kruse (2015) use a “forward looking” method to estimate delayed approvals and “normal” pace adoption counterfactuals. They use Alston et al.’s (2014) global partial equilibrium model to estimate the global demand and supply of soybean used for meals, crushing for oils and oilseeds. They also use Alston et al.’s (1995) formula to estimate the welfare changes in both producer surplus and consumer surplus.

In our study, we adopt the Alston et al. (2014) framework to establish a scenario for SDS resistant soybeans, estimate total soybean demand, supply, and prices in the U.S. historical market, and project historical soybean demand, supply and prices if SDS-resistant soybean were adopted in the past. We follow Alston et al. (1995) to estimate producer and consumer surplus welfare changes as if the SDS-resistant soybean had been adopted in the past.

Scenario development

We assume an individual farmer i is a price-taker and has two options for soybean seeds—conventional or SDS-resistant transgenic. These two options create two different analysis scenarios. We consider planting conventional regular soybean the baseline, or historical, scenario, and planting SDS-resistant transgenic soybean the counterfactual scenario. We define a_{it} as an indicator variable that takes the value of γ when the farmer decides to adopt transgenic soybean seeds, and 1 otherwise, thus:

$$a_{it} = \begin{Bmatrix} \gamma & if\,\pi_{it} \geq FC_{it} \\ 1 & if\,\pi_{it} < FC_{it} \end{Bmatrix} (\gamma \geq 0), \text{ where } \pi_{it} = P_{it}\Delta Y_{it} - Y_{it}\Delta P_{it} - \Delta VC_{it} - \Delta S_{it} - D_{it} \quad (1)$$

where FC_{it} is the fixed cost per acre when the new technology is adopted; π_{it} is the total difference in variable profit in dollars per acre between the new and old technology; P_{it} is the soybean price per bushel in year *t*; D_{it} is the price discount per bushel for the adopted transgenic soybean compared to non-transgenic soybeans; Y_{it} is the average yield of conventional soybeans; ΔY_{it} is the difference in yield per acre between transgenic and conventional soybeans; ΔVC_{it} is the difference in variable cost of production between transgenic and conventional soybeans; and, ΔS_{it} is the difference in seed price per acre between the transgenic and conventional soybeans afforded by farmer *i* in year *t*.

We can reform the above expression as:

$$\pi_{it} = \left(\frac{\Delta Y_{it}}{Y_{it}} - \frac{D_{it}}{P_{it}} - \frac{\Delta VC_{it}}{P_{it}Y_{it}} - \frac{\Delta S_{it}}{P_{it}Y_{it}}\right)P_{it}Y_{it} = (y_{it} - d_{it} - \theta_v v_{it} - \theta_s s_{it})P_{it}Y_{it} \quad (2)$$

where *y* is the proportional change in yield per acre; *d* is the proportional price discount (a premium has a negative value); *v* is the proportional change in variable costs per acre, excluding seeds; and, *s* is the proportional change in seed costs per acre, including technology fees. Then, we can express the total annual net benefits from transgenic soybean adoption for farmer *i* in year *t* (NBA_{it}) as:

$$NBA_{it} = (y_{it} - d_{it} - \theta_v v_{it} - \theta_s s_{it})P_{it}Y_{it}A_{it} - FC_{it} \quad (3)$$

From the individual-level action analysis above, we can deduce the aggregate level of actions.

We can express the total annual farmer benefits as the aggregation of individual farmer's benefits:

$$FB_t = \sum_{i=1}^{n} FB_{it} = \sum_{i=1}^{n} (y_{it} - d_{it} - \theta_v v_{it} - \theta_s s_{it}) P_{it} Y_{it} A_{it} \tag{4}$$

We define K as a proportion of the initial price and marginal cost. Thus, we can express transgenic soybean adoption by incorporating a shifter in the adopter's supply function. K_{it} is defined as:

$$K_{it} = (y_{it} - d_{it} - \theta_v v_{it} - \theta_s s_{it}) \tag{5}$$

Meanwhile, we can express the benefits of the biotech companies as:

$$BB_t = \sum_{i=1}^{n} \theta_s s_{it} P_{it} Y_{it} A_{it} \tag{6}$$

When we sum equations (4) and (6), the benefit of the biotech company is cancelled out, and we can write the total social benefit as:

$$GB_t = FB_t + BB_t = \sum_{i=1}^{n} (y_{it} - d_{it} - \theta_v v_{it}) P_{it} Y_{it} A_{it} \tag{7}$$

Soybean crop sector model

We adopt Alston et al.'s (2014) global partial equilibrium model. Here, we assume that soybean supply is stochastic. We can write the production as:

$$production_t = \widetilde{harvested} \quad area_t * \widetilde{yield}_t \tag{8}$$

As is the case with many crops, farmers often plant more acres than are harvested. To account for that, we define:

$$harvested\tilde{\ }\ area_t = harvest\_planted\_ratio_t * planted\_area_t \tag{9}$$

Then we can aggregate individual farmer's yield and harvested area to get total soybean production:

$$\tilde{Yield} = \sum_{i=1}^{n} \tilde{yield}, \qquad Harvested\tilde{\ }\ Area_t = \sum_{i=1}^{n} harvested\tilde{\ }\ area_t,$$

$$Production_t = Harvested\tilde{\ }\ Area_t * \tilde{Yield}_t$$

Incorporating these elements in Alston et al.'s (2014) global partial equilibrium model, we get:

$$Beginning\ \ Stocks_t = Ending\ \ Stocks_{(t-1)} \qquad \text{(Oilseeds, Meals, and Oils)} \quad (10)$$

$$Soybean\ \ Production_t = Harvested\tilde{\ }\ Area_t * \tilde{Yield}_t \qquad \text{(Oilseeds)} \quad (11)$$

$$Soybean\ \ Meal\ \&\ Oil\ \ Production_t = Crush_t * Crushing\ \ Yield_t \qquad \text{(Meals and Oils)} \quad (12)$$

$$Total\ \ Supply_t = Beginning\ \ Stocks_t + Production_t + Imports_t \quad \text{(Oilseeds, Meals, and Oils)} \quad (13)$$

$$\begin{aligned} Total\ \ Demand_t &= Crush_t + Food\ \ Use_t + Other\ \ Use_t \\ &+ Exports_t + Ending\ \ Stocks_t \end{aligned} \qquad \text{(Oilseeds)} \quad (14)$$

$$\begin{aligned} Total\ \ Demand_t &= Food\ \ Use_t + Feed\ \ Use_t + Industrial\ \ Use_t \\ &+ Exports_t + Ending\ \ Stocks_t \end{aligned} \qquad \text{(Meals and Oils)} \quad (15)$$

$$\begin{aligned} Domestic\ \ Use_t &= Crush_t + Food\ \ Use_t + Other\ \ Use_t \\ &+ Ending\ \ Stocks_t \end{aligned} \qquad \text{(Oilseeds)} \quad (16)$$

$$\begin{aligned} Domestic\ \ Use_t &= Food\ \ Use_t + Feed\ \ Use_t + Industrial\ \ Use_t \\ &+ Ending\ \ Stocks_t \end{aligned} \qquad \text{(Meals and Oils)} \quad (17)$$

As defined in equation (5), K can be taken as the percentage vertical shift in the supply function of the transgenic soybean. Thus, following Alston et al. (1995), we can estimate the changes in soybean producer surplus caused by the adoption of SDS-resistant soybean seeds as follows:

$$\Delta PS_{R,S} = P_0 Q_{R,0}(K - Z)(1 + 0.5Z\varepsilon_S) \tag{18}$$

where ΔPS is the change in producer surplus; R is the region of interest; S is soybeans; P_0 is the counterfactual price; P_1 is the actual price; ε_S is soybean supply elasticity; and, Z is defined as $Z = -\frac{(P_1 - P_0)}{P_0}$.

We can estimate the change in soybean consumer surplus using

$$\Delta CS_{R,S} = P_0 Q_{R,0} Z(1 + 0.5Z\eta) \tag{19}$$

where ΔCS is the change in consumer surplus and η is the absolute value of soybean demand elasticity.

Data and Results

We obtain critical variables' linear equation estimations for the model by performing OLS regressions using USDA's World Agricultural Supply and Demand Estimates (WASDE) data on soybean yield, harvested area, stocks, exports, food and other use, prices, etc., and borrowing the FAPRI (2019) model structure. The data cover the years from 2000 to 2017. Our aim is to obtain the best fitting linear equation estimations and use these estimated models to simulate the historical values of critical soybean variables, like planted area, beginning and ending stocks, crush, export, import, food and other use, and then extend these estimated models to simulate the counterfactual scenario presuming that the SDS resistant soybean variety had been adopted earlier in history. The FAPRI model structure has been used as it is a well-known projection model. We also take into account the nature of the time series of the underlying variables. For example, we model the GDP deflator as an AR(1) process. By comparing the simple linear model form and more complicated format of stochastic trends in the other critical variables, like beginning and ending stocks, we found that the simple linear models were the best fitting model format and were easy to use, thus they're adopted. Tables 1–8 report the regression results and the corresponding statistics. Below, we summarize the conditions for equilibrium in the soybean sector.

Supply side

$$\Pr oduction_t = Yield_t * Harvested \quad Area_t = Yield_t * Harvest\_planted\_ratio_t * Planted\_area_t \tag{20}$$

$$Total \quad Supply_t = \Pr oduction_t + beginning\_stocks_t \tag{21}$$

Demand side:

$$Total \quad Demand_t = crush_t + \exp ort_t + ending\_stocks_t + food\_other\_use_t \tag{22}$$

Equilibrium:

$$Total \quad Supply_t = Total \quad Demand_t \tag{23}$$

Historical Estimation

Baseline scenario analysis

In the baseline scenario, we assume that SDS-resistant transgenic soybeans are not adopted; thus, only conventional soybeans are planted. So this scenario is just the estimation of the historical soybean market. Then soybean production yield is the value of the actual yield of SDS-affected soybeans, which we obtain from the WASDE report. The WASDE report also provides the underlying data for both soybean supply and demand. Table 9 and figures 3, 4, and 5a–5c show results of using the model above.

To obtain estimated prices and total soybean supply, we input a series of soybean prices in the model and calculate total supply and demand based on these prices and the estimated equations. Then, we adjust the price series until total supply balances with total demand. The estimated market equilibrium prices are the prices that make total supply equal total demand.

Table 9 and figure 3 show that the model estimation of soybean prices works well, as estimated soybean prices do not deviate much from historical soybean prices

Table 9 and figures 4 show estimated and actual soybean equilibrium supply. In equilibrium, total market supply and demand are equal; thus, it is more useful to depict market demand components. Table 9 and figures 5a–5c show major components of soybean demand, like soybean crush, export, and ending stocks. Figure 4 shows that estimated supply tracts well with the historical values. As figures 5a–5c show, simulated soybean crush, export, and ending stocks are also close to historical data.

Counterfactual scenario analysis

There are no market price data available for SDS-resistant transgenic soybeans, as it is a newly developed variety. Thus, we have to simulate market prices to estimate how adoption would have affected price levels in the past. Given that the model estimation in the baseline scenario, we can extend it to simulate SDS-resistant transgenic soybean market prices.

For the counterfactual scenario, we assume that farmers adopt SDS-resistant transgenic soybean in 50% of soybean planted acres. As the SDS-resistant transgenic soybean is expected to recover 50% of SDS losses in soybean yield. And also, since only part of the country is affected by SDS and the SDS resistant variety is only adopted in those areas, the average yield of the whole nation will be the weighted average of the counter factual scenario yield and the baseline scenario yield. The counterfactual scenario yield is:

$$Yield_{counterfactual}=0.5*Yield_{baseline}+0.5*(Yield_{baseline}+0.5*SDS\ Losses) \quad (24)$$

And if we take into account the areas not affected by SDS, then the national weighted average yield is:

$$Yield_{average}=Yield_{counterfactual}*L+Yield_{baseline}*(1-L) \quad (25)$$

Here, L represents the percentage loss in soybean production caused by SDS, which is reported in the first column of Table 10b. This yield is greater than the baseline scenario yield; hence, it increases soybean production and total supply.

We change soybean yield to match the assumption above, use the SDS-resistant transgenic soybean variable cost of production, and replace soybean yield and variable cost of production in the baseline scenario to revise historical estimates. After SDS-resistant soybean adoption, the net return will change to:

$$SBENRS_{scenario1} = soybean\_price * soybean\_yield_{scenario1} - soybean\_variable cost_{scenario1} \quad (26)$$

Soybean production will change to:

$$Production = Yield_{scenario1} * Harvested\ \ Area = Yield_{scenario1} * Harvest\_planted\_ratio * Planted\_area_{scenario1} \quad (27)$$

The remainder of the partial equilibrium model is unchanged. Note that in equation (20), $Planted\_area_{scenario1}$ means I replaced soybean net return $SBENRS$ with $SBENRS_{scenario1}$, while all other terms remain unchanged.

We summarize the values and percentage changes of soybean price, soybean total supply, soybean crush, soybean export and soybean ending stocks in Tables 10b for the case that SDS resistant variety is adopted in the affected areas. We can see from the tables that if adopted in the affected areas, the effects of the adoption of the new variety are relatively small. The market price will be about 0.1% lower than baseline projected level (on average, 0.13% lower), and the total supply will be about 0.1%-0.5% (on average, 0.19%) higher than baseline projected level. And the adoption of the SDS resistant variety in the affected planted areas will decrease crush, increase export, and increase ending stocks by 0%-0.2% (on average, 0.06%), 0.1%-0.4% (on average, 0.17%), and 0.1%-3.8% (on average, 1.04%) respectively. The results are reasonable because the adoption of SDS-resistant transgenic soybean partially restores SDS losses; hence, adoption increases total soybean supply and shifts the total supply curve outward. With the increase in supply, soybean market price falls with adoption. Crush demand falls with reduced crushing profitability in the soybean meal and oil markets. A lower market price also increases exports, as foreign consumers are willing to purchase soybeans at cheaper prices. Furthermore, stocks increase as the growth in supply exceeds the growth in usage.

Welfare Analysis

Using the methodology behind Alston et al. (1995) and Alston et al. (2014), , we can use equations (18) and (19) to estimate changes in producer and consumer surplus, if the SDS-resistant transgenic soybeans were adopted in the past. Table 11 and Figure 6 show results of the producer and consumer surplus changes.

The welfare results show that changes in soybean producer surplus are always positive and take relatively high values; furthermore, the changes in consumer surplus are also positive, but smaller than producer surplus changes in general. Table 10b shows the percentage change of soybean prices and soybean supply and summarizes the historical average values. Soybean producers benefit from increased yields and lower production costs, which more than offset the lower soybean price. Furthermore, consumers benefit from a 0.13% decrease in soybean market price. In total, producers benefit more from SDS-resistant soybean adoption than consumers. The change in soybean producer surplus peak in years where there were significant SDS losses, as shown in figure 2. This finding is consistent with Alston et al. (2014). Figure 6 shows that the scale of producer and consumer surplus changes gradually increase over time, in general. This indicates that the benefits of SDS-resistant soybean adoption for the whole economy will increase over time.

Conclusion

We use a soybean crop sector model to estimate soybean prices and total supply and demand and explore the potential impacts of the adoption of SDS resistant soybeans.

The adoption of SDS-resistant transgenic soybean will restore part of yield losses caused by Sudden Death Syndrome, thus slightly increasing the soybean total supply. Since demand does not increase in proportion to the supply change, the increase in total supply leads to a decrease in the price of soybeans. The results indicate that projected soybean prices are, in general, 0.1% lower than historical soybean prices; and, that projected soybean supplies are 0.1%–0.5% higher than historical supplies. Projected crush, export, and ending stocks are 0%–0.2% lower, 0.1%–0.4% higher, and 0.1%–3.8% higher, respectively, than historical data.

The welfare analysis indicates that if the SDS-resistant transgenic soybean variety had been adopted in the past, they would have brought small scales of benefits to producers and relatively smaller scales of benefits to consumers. The benefits to soybean producers would have peaked in years when historical SDS losses were large. In general, the scales of benefits brought to producers and consumers would gradually enlarge with SDS-resistant soybean adoption. This implies that potential benefits SDS-resistant soybean adoption become larger as time passes.

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Figures and Tables

Table 1. Planted Area: Variables, Coefficients, and T-Statistics

Planted Area	Full name	Coefficient	T-statistics
$BRENRS_{-1}$	Barley net return	0.11	1.97
$CRENRS_{-1}$	Corn net return	-0.03	-1.09
$CTENRS_{-1}$	Cotton net return	0.00	0.15
$OTENRS_{-1}$	Oats net return	0.02	0.66
$PNENRS_{-1}$	Peanuts net return	-0.01	-1.37
$RCENRS_{-1}$	Rice net return	-0.02	-1.38
$SBENRS_{-1}$	Soybean net return	0.02	3.34
$SGENRS_{-1}$	Sorghum net return	0.02	0.34
$WHENRS_{-1}$	Wheat net return	0.01	0.13
Constant		72.27	17.68
R^2		0.75	
F(9, 8)		2.69	

Source: WASDE report and author's calculation 2000-2017.
Notes: Here, the subscript (-i) (i=1, 2, 3, 4…) represents the same item in the last i period. jNRS-1 represents the net return of crop j, and the subscript -1 is the net return of period t-1 (current period is t). The net return of any crop is the difference between its gross return and its variable cost. For example, $SBENRS = soybean\_price * soybean\_yield - soybean\_variable cost$.

Table 2. Beginning Stocks: Variables, Coefficients, and T-Statistics

Beginning_Stocks	Coefficient	T-statistics
$Beginning\_Stocks_{-1}$	0.54	2.69
$PDCGNP_{-1}/Price_{-1}$	13.61	1.95
$Import_{-1}$	-2.68	-1.46
$Production_{-1}$	0.19	3.79
Constant	-633.54	-3.52
R^2	0.69	
F(4, 13)	7.22	

Source: WASDE report and author's calculation 2000-2017.

Table 3. Estimated Crush: Variables, Coefficients, and T-Statistics

Crush	Coefficient	T-statistics
$Crush_{-1}$	0.05	0.32
Crush_term2	36.61	0.75
$Total\_supply_{-1}$	0.25	3.61
Year-2000	2.10	0.21
$Export_{-1}$	-0.13	-1.89
Food&other_use	0.66	1.44
Constant	761.27	2.21
R^2	0.92	
F(6, 11)	21.17	

Source: WASDE report and author's calculation 2000-2017.

Note: $Crush\_term2 = (SMP48d * \frac{SMCYLD}{2000} + SOPMKT * \frac{SOCYLD}{100} - price) / PDCGNP_{-1}$

$SMP48d$ is the soybean meal 48% price; $SMCYLD$ is the soymeal crush yield; $SOPMKT$ is the soybean oil market price; $SOCYLD$ is the soybean oil crush yield; and, $PDCGNP$ is the GDP deflator.

Table 4. Estimated Export: Variables, Coefficients, and T-Statistics

Export	Coefficient	T-statistics
$Export_{-1}$	0.79	6.88
$SMP48d_{-1}$	64.22	0.78
$Price_{-1}$	-2.81	-0.02
$SOPMKT_{-1}$	-11.60	-0.82
$Cornprice_{-1}$	-45.26	-0.48
$Wheatprice_{-1}$	25.38	0.58
Constant	56.44	0.42
R^2	0.93	
F(6, 11)	24.64	

Source: WASDE report and author's calculation 2000-2017.

Note: SMP48d and SOPMKT are explained in Table 3 notes.

Table 5. Estimated Import: Variables, Coefficients, and T-Statistics

Import	Coefficient	T-statistics
$Import_{-1}$	0.30	1.25
Price	-3.32	-1.68
$Price_{-1}$	5.84	3.08
Year-2000	0.18	0.17
Constant	-10.10	-1.21
R^2	0.75	
F(4, 13)	9.76	

Source: WASDE report and author's calculation 2000-2017.

Table 6. Estimated Ending Stocks: Variables, Coefficients, and T-Statistics

Ending_Stocks	Coefficient	T-statistics
$Ending\_Stocks_{-1}$	0.54	2.69
PDCGNP/Price	13.61	1.95
Import	-2.68	-1.46
Production	0.19	3.79
Constant	-633.54	-3.52
R^2	0.69	
F(4, 13)	7.22	

Source: WASDE report and author's calculation 2000-2017.

Table 7. Estimated Food and Other Uses: Variables, Coefficients, and T-Statistics

Food&other_use	Coefficient	T-statistics
Planted_area	-2.13	-1.57
Price/PDCGNP	-977.13	-4.56
Constant	310.94	4.21
R^2	0.72	
F(3, 13)	10.89	

Source: WASDE report and author's calculation 2000-2017.

Table 8. Estimated GDP Deflator: Variables, Coefficients, and T-Statistics

PDCGNP	Coefficient	T-statistics
$PDCGNP_{-1}$	0.98	82.55
Constant	3.30	2.86
R^2	0.998	
F(1, 17)	6814.28	

Source: WASDE report and author's calculation 2000-2017.

Table 9. Model Projections of the Soybean Market Compared to the Historical Data

Year	Historical Price	Projected Price	Historical Total Supply	Projected Total Supply	Historical Crush	Projected Crush	Historical Export	Projected Export	Historical Ending Stocks	Projected Ending Stocks
2000	4.54	4.44	3,051.54	3,178.39	1,639.67	1,669.83	995.87	924.65	247.75	305.55
2001	4.38	4.19	3,140.75	3,306.56	1,699.74	1,686.41	1,063.65	948.96	208.06	387.29
2002	5.53	5.44	2,968.87	3,075.85	1,614.79	1,706.73	1,044.37	989.05	178.33	279.22
2003	7.34	7.53	2,637.74	2,871.26	1,529.70	1,634.38	886.55	986.80	112.41	45.10
2004	5.74	5.56	3,241.78	3,340.04	1,696.08	1,550.61	1,097.16	996.77	255.74	271.18
2005	5.66	5.75	3,327.45	3,239.10	1,738.85	1,751.68	939.88	1,034.64	449.33	263.79
2006	6.43	6.03	3,655.09	3,525.86	1,807.71	1,806.18	1,116.50	923.18	573.81	536.30
2007	10.10	10.37	3,260.80	3,325.95	1,803.41	1,844.77	1,158.83	1,082.71	205.03	269.76
2008	9.97	10.01	3,185.30	3,531.95	1,661.92	1,691.38	1,279.29	1,294.57	138.20	138.23
2009	9.59	9.47	3,513.72	3,644.67	1,751.69	1,657.37	1,499.05	1,385.11	150.89	214.91
2010	11.30	10.75	3,496.64	3,442.69	1,648.04	1,725.71	1,504.98	1,480.12	215.01	250.74
2011	12.50	12.73	3,328.32	3,490.50	1,703.02	1,727.83	1,365.25	1,494.55	169.37	178.11
2012	14.40	14.38	3,251.95	3,410.02	1,688.90	1,681.37	1,327.53	1,471.44	140.56	105.55
2013	13.00	12.83	3,570.23	3,480.82	1,733.89	1,670.87	1,637.83	1,526.86	91.99	82.83
2014	10.10	9.65	4,052.31	4,223.56	1,873.49	1,724.90	1,843.38	1,841.89	190.61	209.40
2015	8.95	9.25	4,140.49	4,135.44	1,886.00	1,862.05	1,942.00	1,820.86	197.00	223.74
2016	9.47	8.98	4,515.06	4,583.70	1,901.00	1,856.12	2,174.00	1,775.74	302.00	388.49
2017	9.30	9.45	4,693.55	4,477.23	1,960.00	1,935.96	2,065.00	1,913.71	555.00	463.16

Source: WASDE report and author's calculation.
Note: Prices are in $/bushel and all other variables are in million bushels.

Table 10a. Projected Prices, Total Supply and Components of Soybean Demand in Counterfactual Scenario, as Compared to Baseline Projection

Year	Projected Price (Regular)	Projected Price (SDS)	Projected Total Supply (Regular)	Projected Total Supply (SDS)	Projected Crush (Regular)	Projected Crush (SDS)	Projected Export (Regular)	Projected Export (SDS)	Projected Ending Stocks (Regular)	Projected Ending Stocks (SDS)
2000	4.44	4.43	3,178.39	3190.24	1,669.83	1668.29	924.65	927.83	305.55	317.21
2001	4.19	4.19	3,306.56	3311.59	1,686.41	1685.61	948.96	949.58	387.29	391.05
2002	5.44	5.43	3,075.85	3080.36	1,706.73	1706.79	989.05	990.56	279.22	284.92
2003	7.53	7.53	2,871.26	2873.56	1,634.38	1634.50	986.80	988.58	45.10	44.98
2004	5.56	5.55	3,340.04	3346.58	1,550.61	1547.83	996.77	998.18	271.18	274.09
2005	5.75	5.74	3,239.10	3242.32	1,751.68	1751.18	1,034.64	1036.88	263.79	263.59
2006	6.03	6.02	3,525.86	3529.77	1,806.18	1805.39	923.18	923.22	536.30	536.82
2007	10.37	10.35	3,325.95	3332.27	1,844.77	1844.34	1,082.71	1083.88	269.76	272.03
2008	10.01	10.00	3,531.95	3539.58	1,691.38	1690.99	1,294.57	1296.69	138.23	139.15
2009	9.47	9.45	3,644.67	3649.03	1,657.37	1655.64	1,385.11	1386.93	214.91	216.80
2010	10.75	10.73	3,442.69	3460.42	1,725.71	1725.49	1,480.12	1486.19	250.74	259.29
2011	12.73	12.71	3,490.50	3497.76	1,727.83	1727.38	1,494.55	1498.03	178.11	179.24
2012	14.38	14.37	3,410.02	3415.25	1,681.37	1680.76	1,471.44	1474.96	105.55	105.97
2013	12.83	12.82	3,480.82	3485.05	1,670.87	1669.66	1,526.86	1528.65	82.83	82.90
2014	9.65	9.63	4,223.56	4241.46	1,724.90	1721.49	1,841.89	1848.17	209.40	214.11
2015	9.25	9.24	4,135.44	4144.84	1,862.05	1860.75	1,820.86	1823.66	223.74	227.74
2016	8.98	8.98	4,583.70	4584.10	1,856.12	1856.02	1,775.74	1775.74	388.49	388.55
2017	9.45	9.45	4,477.23	4482.05	1,935.96	1935.15	1,913.71	1915.30	463.16	463.68

Source: WASDE report and author's calculation.
Note: Price is in $/bushel, the others are in million bushels.

Table 10b. Percentage Change in Counterfactual Scenario

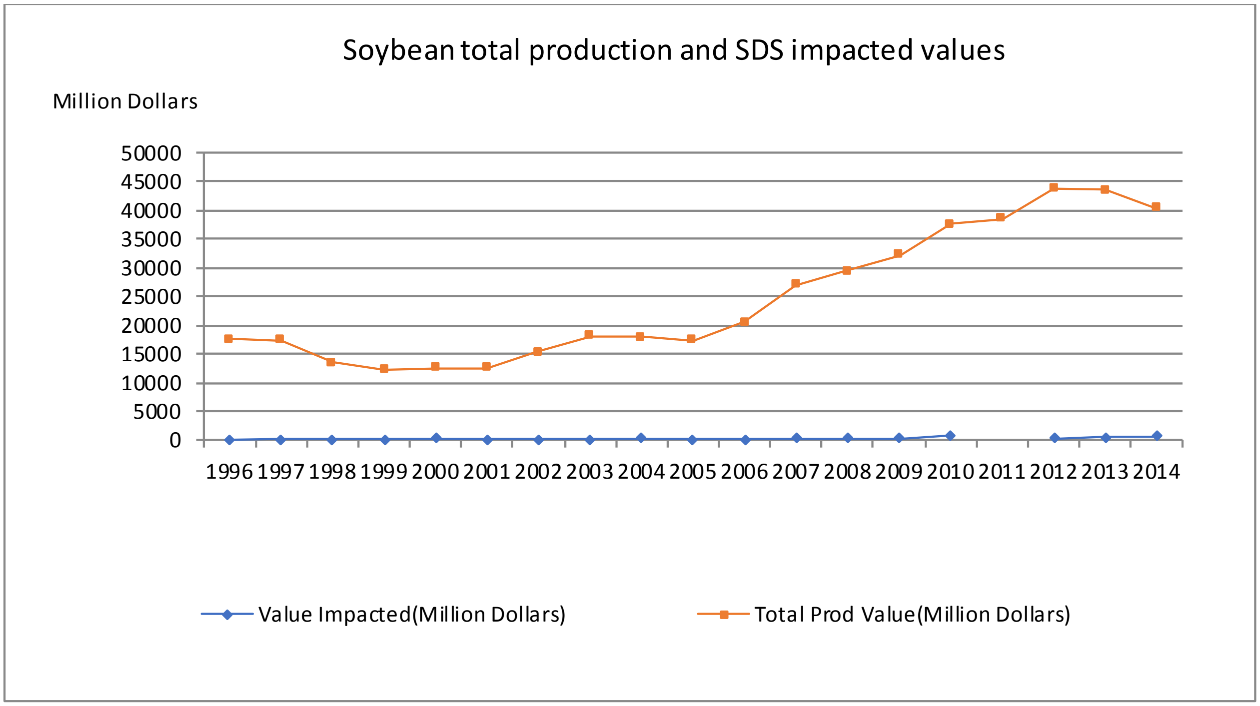
Year	% SDS Losses to production	Price Percentage Difference	Supply Percentage Difference	Crush Percentage Difference	Export Percentage Difference	Projected Ending Stocks Percentage Difference
2000	2.75%	-0.25%	0.37%	-0.09%	0.34%	3.82%
2001	0.81%	-0.09%	0.15%	-0.05%	0.06%	0.97%
2002	1.04%	-0.16%	0.15%	0.00%	0.15%	2.04%
2003	0.51%	-0.04%	0.08%	0.01%	0.18%	-0.27%
2004	1.36%	-0.16%	0.20%	-0.18%	0.14%	1.07%
2005	0.65%	-0.07%	0.10%	-0.03%	0.22%	-0.07%
2006	0.85%	-0.11%	0.11%	-0.04%	0.01%	0.10%
2007	0.82%	-0.11%	0.19%	-0.02%	0.11%	0.84%
2008	0.69%	-0.10%	0.22%	-0.02%	0.16%	0.66%
2009	1.03%	-0.12%	0.12%	-0.10%	0.13%	0.88%
2010	2.10%	-0.25%	0.52%	-0.01%	0.41%	3.41%
2011	0.71%	-0.10%	0.21%	-0.03%	0.23%	0.63%
2012	0.67%	-0.09%	0.15%	-0.04%	0.24%	0.40%
2013	0.85%	-0.12%	0.12%	-0.07%	0.12%	0.08%
2014	1.57%	-0.23%	0.42%	-0.20%	0.34%	2.25%
2015	1.11%	-0.14%	0.23%	-0.07%	0.15%	1.79%
2016	0.07%	-0.01%	0.01%	-0.01%	0.00%	0.02%
2017	0.67%	-0.09%	0.11%	-0.04%	0.08%	0.11%
Average	1.02%	-0.13%	0.19%	-0.06%	0.17%	1.04%

Source: WASDE report and author's calculation.

Table 11. Welfare Analysis of the Adoption of SDS-Resistant Transgenic Soybean

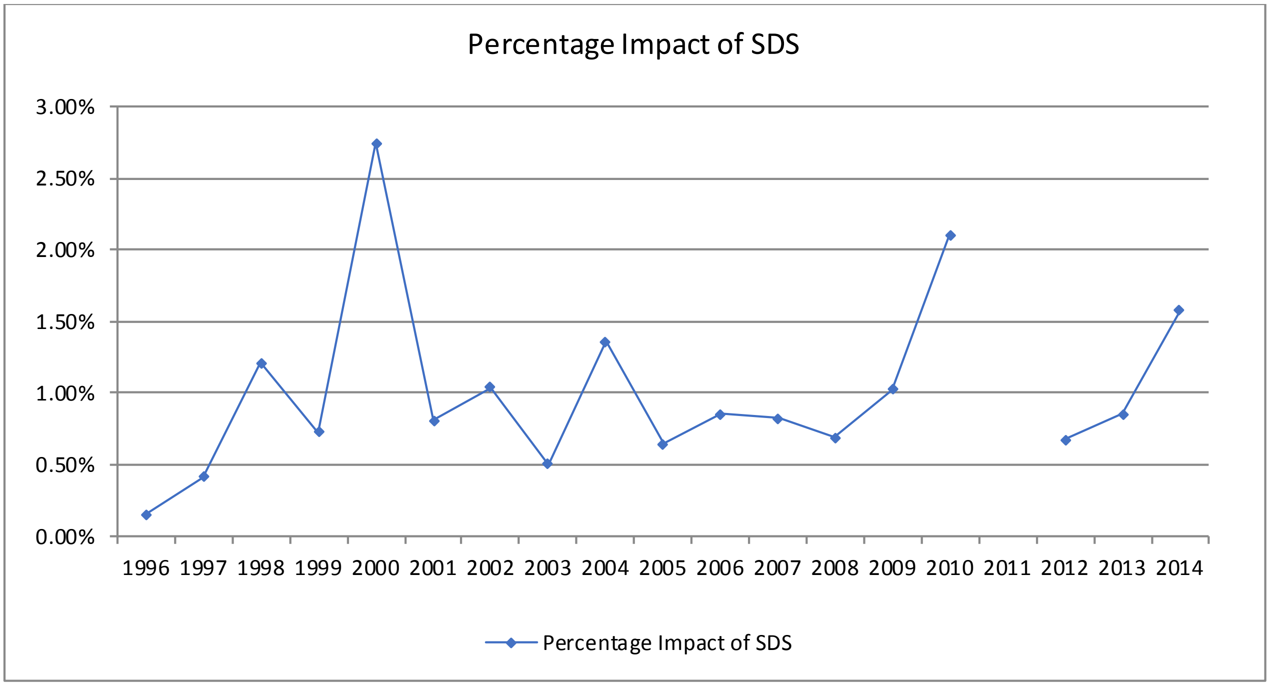
Year	Change in Producer Surplus ($ million)	Change in Consumer Surplus ($ million)
2000	175.18	40.48
2001	13.62	0.36
2002	27.44	0.43
2003	9.87	0.05
2004	61.60	3.02
2005	13.75	0.01
2006	27.73	0.51
2007	41.00	0.23
2008	36.79	0.74
2009	62.04	8.92
2010	302.66	104.06
2011	59.25	7.88
2012	52.85	5.52
2013	74.46	14.30
2014	246.99	97.71
2015	104.10	26.20
2016	7.61	1.73
2017	46.55	4.27

Source: WASDE report and author's calculation.



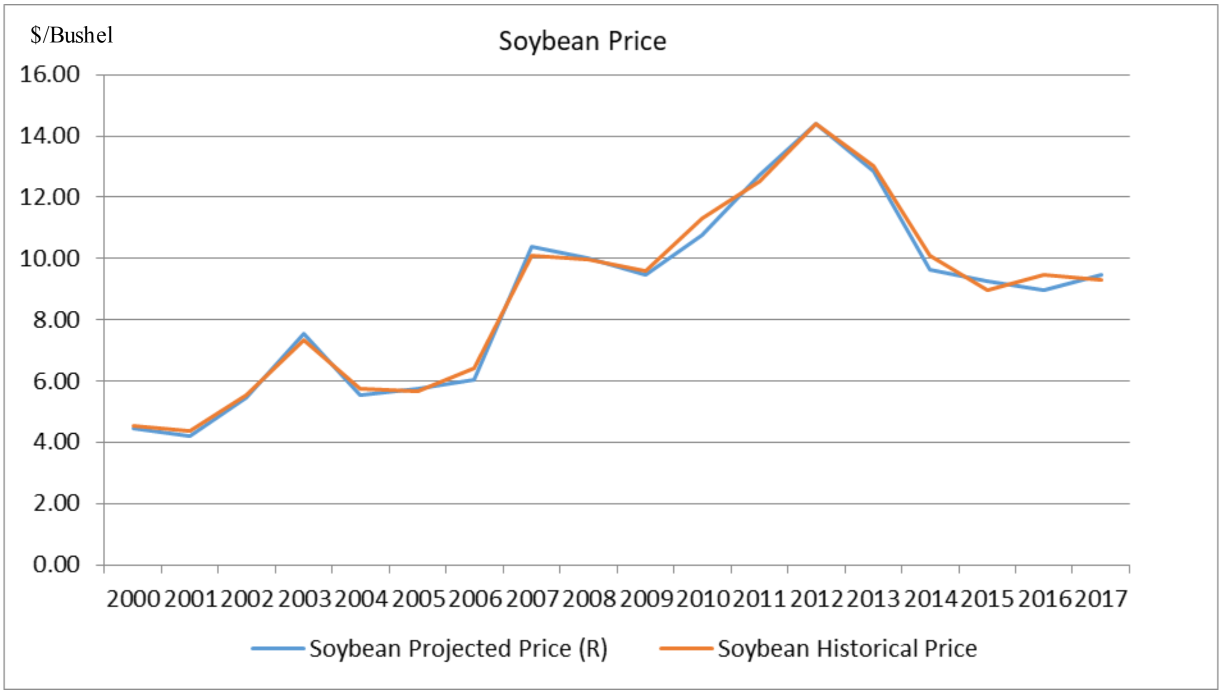
Source: USDA-Risk Management Agency.

Figure 1. Total soybean production value and SDS-impacted value



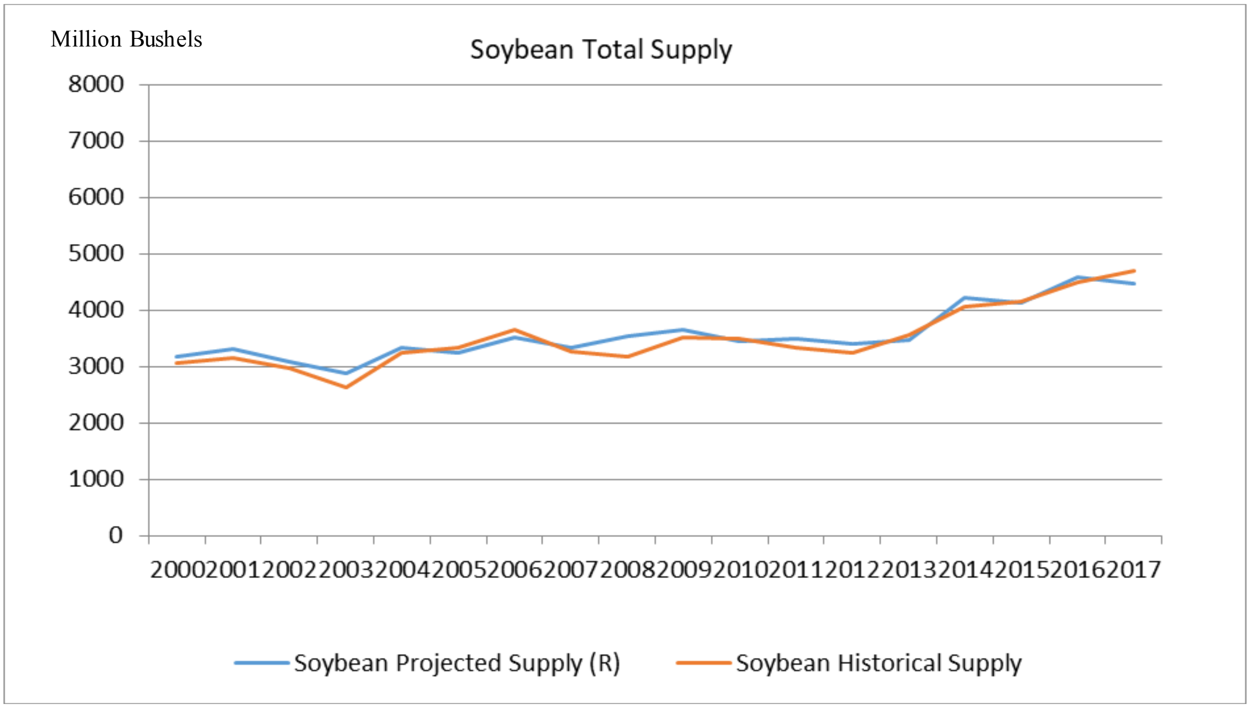
Source: USDA-Risk Management Agency.

Figure 2. Percentage impact of SDS in soybean production



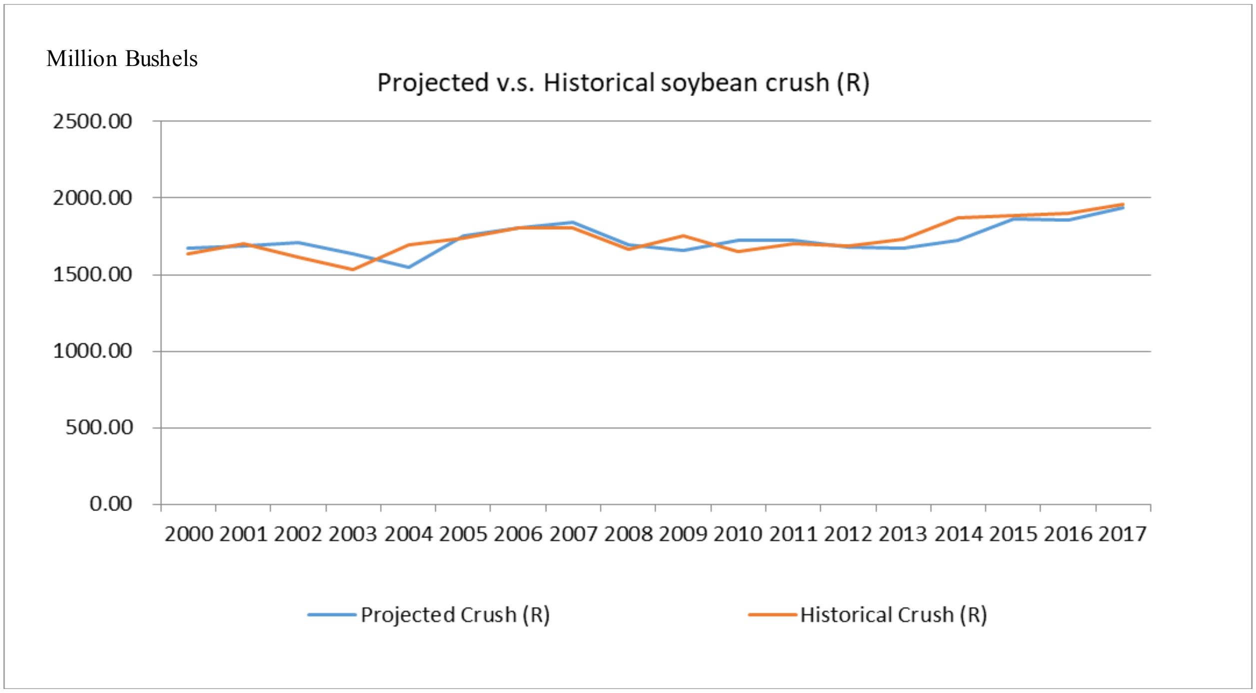
Source: WASDE report and author's calculations.

Figure 3. Estimated and historical soybean prices



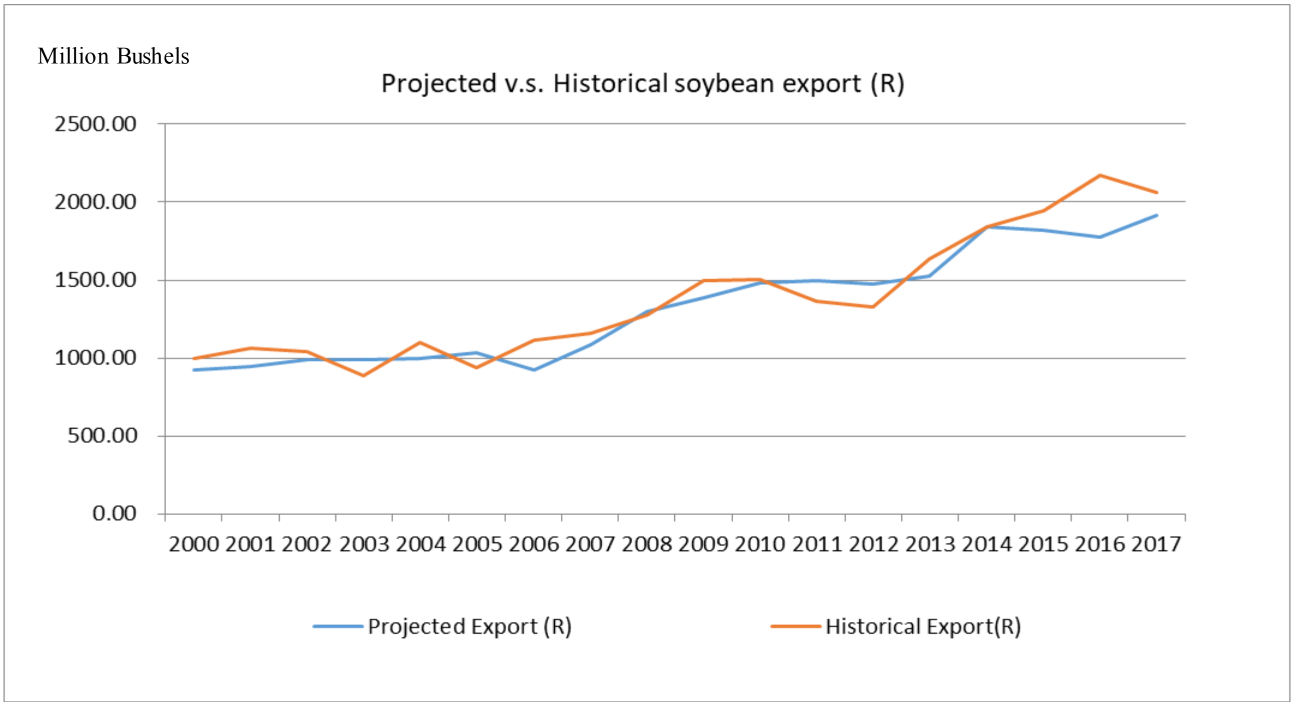
Source: WASDE report and author's calculations.

Figure 4. Projected and historical soybean total supply



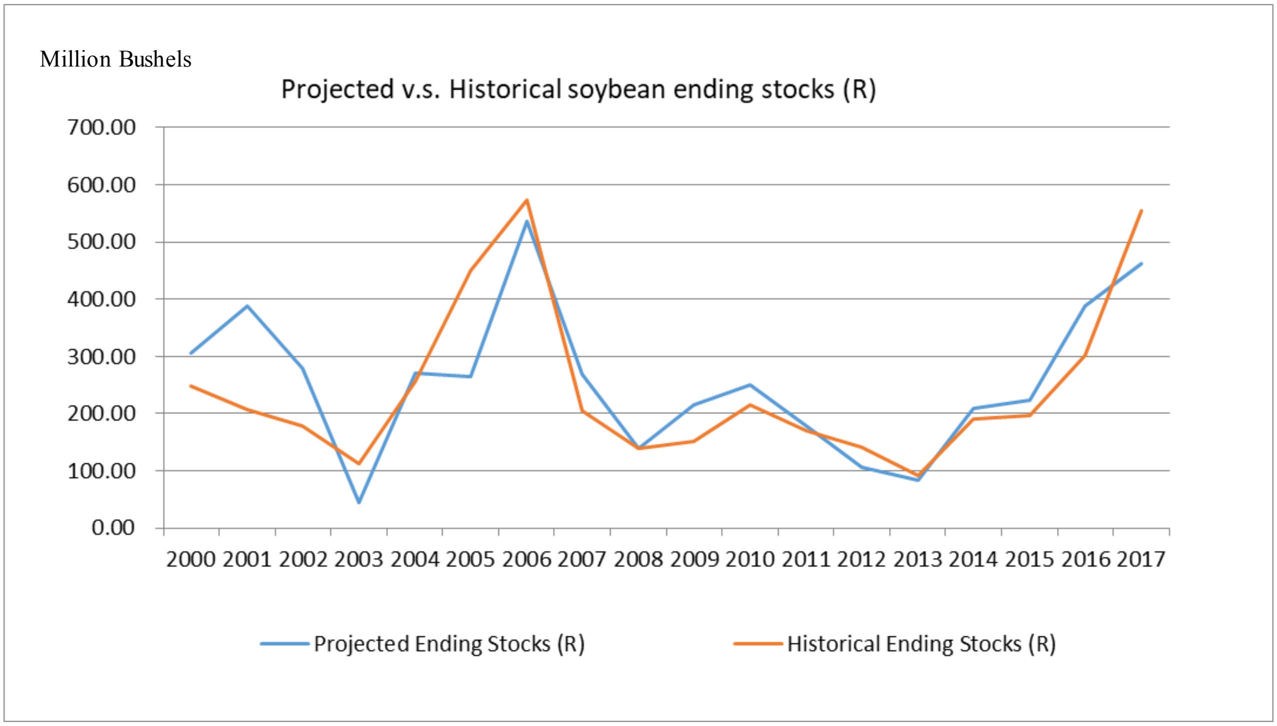
Source: WASDE report and author's calculations.

Figure 5a. Projected and historical soybean crush



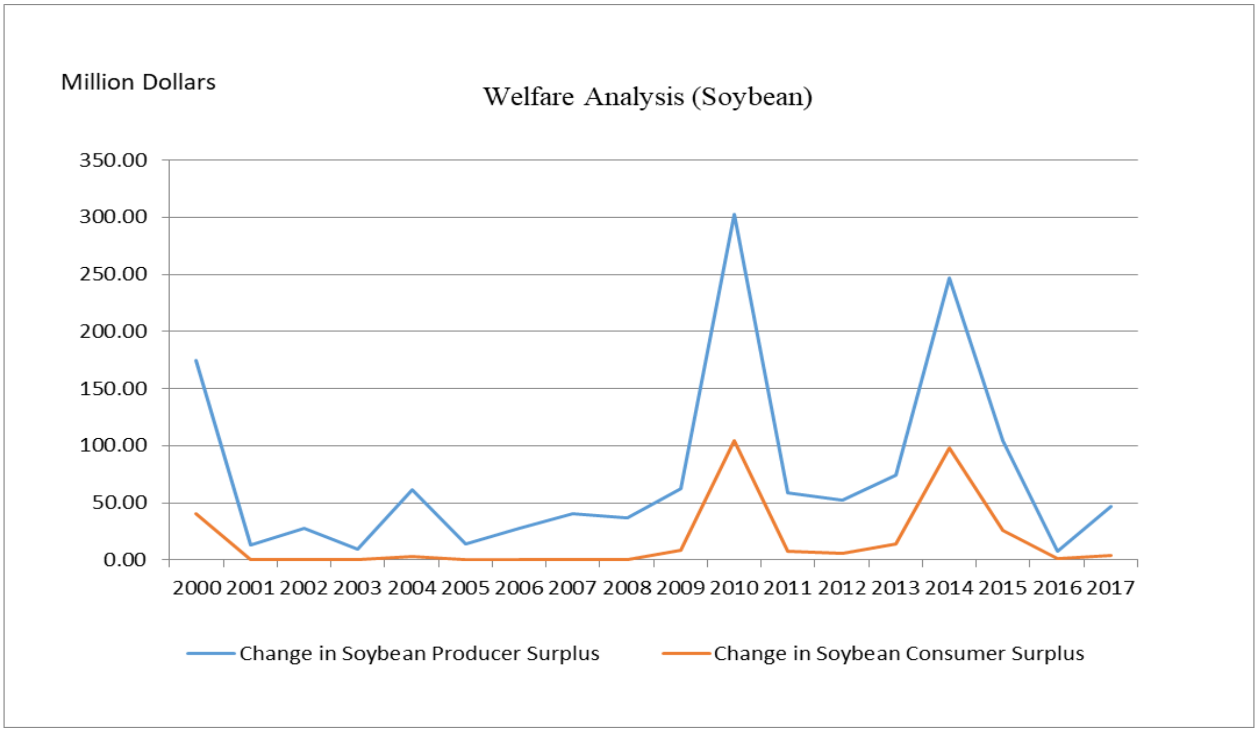
Source: WASDE report and author's calculations.

Figure 5b. Projected and historical soybean exports



Source: WASDE report and author's calculations.

Figure 5c. Projected and historical soybean ending stocks



Source: author's calculations.

Figure 6. Welfare analysis of SDS-resistant transgenic soybean adoption

CHAPTER 5. GENERAL CONCLUSION

In this dissertation, we have already addressed in each of the following chapters respectively the questions proposed in Chapter 1. In Chapter 2, we have studied the effects that the four objective measures of treatment, relative income, as well as observed and unobserved income inequalities and demographic attributes on Chinese workers' job satisfaction, promotion satisfaction and social status. We found income inequality did not have statistically significant impacts on Chinese workers' job satisfaction, promotion satisfaction and social status, and the effects that income inequality had on the three employment perception measures of Chinese workers differ by its observability; meanwhile, the unobserved objective measure of treatment and the observed measure of relative wage both have positive and significant impacts on Chinese workers' job satisfaction, promotion satisfaction and social status, indicating Chinese workers raise their personal well-being by receiving an overpayment from the market fair wage based on their skills or a wage paid above the provincial average. Moreover, just like the cases in developed market economies, Chinese workers' employment perceptions are nearly uncorrelated with market information. In Chapter 3, we investigated Chinese consumer's meat consumption patterns and their changes over the years. We found that pork and other meats were necessities, while beef, mutton and chicken were luxury goods. As household income increased, meat expenditure enlarged and pork captured a larger share of the total expenditure caused by rapidly rising beef, mutton and chicken prices. The results implied that with the agreement to waive China's retaliatory tariff on U.S. pork export, the U.S. pork industry would see great opportunities for growth. In Chapter 4, we learned the potential economic impacts of adopting SDS resistant soybean. We found that if the SDS resistant variety were adopted to confront Sudden Death Syndrome, the increase in production would reduce price, increase supply, and raise up export in the U.S. soybean market. Moreover, adopting SDS resistant soybean would bring more benefits to the producers than to the consumers. With China's agreement to waive the tariffs imposed on U.S. soybean export, China's demand on the U.S. soybean would increase rapidly and thus bring much better opportunities for the U.S soybean market to grow. So, it would be beneficial to adopt the SDS resistant transgenic soybean variety to confront the Sudden Death Syndrome, especially at this special moment.