AN INTEGRATED STUDY OF AVIAN INFLUENZA IMPACTS

AND ASSOCIATED CLIMATE CHANGE ISSUES

A Dissertation

by

JIANHONG MU

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2012

Major Subject: Agricultural Economics

An Integrated Study of Avian Influenza Impacts and Associated Climate Change Issues

AN INTEGRATED STUDY OF AVIAN INFLUENZA IMPACTS

AND ASSOCIATED CLIMATE CHANGE ISSUES

A Dissertation

by

JIANHONG MU

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Approved by:

Chair of Committee,	Bruce A. McCarl
Committee Members,	David Bessler
	Ximing Wu
	Yanhong Jin
	Bo Norby
Head of Department,	John Nichols

May 2012

Major Subject: Agricultural Economics

ABSTRACT

An Integrated Study of Avian Influenza Impacts and Associated Climate Change Issues.

(May 2012)

Jianhong Mu, B.A., Renmin University of China;

M.S., Renmin University of China

Chair of Advisory Committee: Dr. Bruce A. McCarl

This dissertation examines issues related to avian influenza (AI) disease. This is done via three essays that individually examine: (1) the impacts of climate change on the probability and expected numbers of AI outbreaks and associated economic loss; (2) the effects that media coverage of AI outbreaks has on meat demand in the United States, and (3) the potential effectiveness of AI mitigation strategies on poultry production and welfare under a simulated AI outbreak in United States.

The climate change and spread of AI outbreaks study finds that the probability and expected number of AI outbreaks increases as climate change proceeds. Particularly, past climate change has contributed to the current spread of AI disease by 11% and the future climate change will increase this spread by another 12%. Moreover, the underreporting probability of AI outbreaks is also examined and results show that the underreporting probability is much higher in countries with lower gross domestic production level, larger export of poultry products and more numbers of AI confirmed

human deaths. Therefore, disease prevention and control plans should focus on these economically poor and climatically changed regions.

AI outbreak information has significant effects on meat demand in the United States. In particular, impacts of overseas AI human deaths on meat demand equal 0.02% for beef, -0.005% for pork, and -0.01% for chicken for sample when there was no AI occurred in the United States, while it has smaller impacts on meat expenditure when using the whole sample. In addition, human deaths due to AI disease will increase beef demand and decrease that for pork and chicken. However, AI media coverage in short-run has insignificant effect on meat demand, which suggests that consumers are more cautious when cases occur within the United States as opposed to international cases.

In the study on the effects and welfare implications of AI mitigation strategies, results find that vaccination strategy is welfare decreasing under most cases of demand shocks but is desirable in some regions when both domestic and excess demand decrease. Under the assumption of one AI outbreak in the United States, the associated mitigation costs because of past climate change are relatively small.

DEDICATION

To my parents, elder sister and her family, younger brother and Fang Tang

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my advisor, Dr. Bruce McCarl, for his excellent guidance, caring, patience, and financial support for my research through the past four years. I feel so lucky to have Dr. McCarl as my advisor and am very grateful for all he has done. I would never have been able to finish my dissertation without his guidance.

I would also like to thank all my committee members for their guidance and support throughout the course of this research. Special thanks goes to Dr. David Bessler for his advice on times series models; Dr. Ximing Wu for his comments and suggestions in solving my econometric questions; Dr. Yanhong Jin for sharing her meat demand data and encouragement through this journey; and Dr. Bo Norby for his comments on avian influenza disease.

Thanks also go to my friends Drs. Isabelle Tsakok and. Huijun Pan for their valuable comments as well as supports for my research, my colleagues Drs. Aklesso Egbendewe-Mondzozo, Amy Hagerman, Yuquan Zhang and Attavanich Witsanu for working together on book chapters, reviews and projects that have benefited this research. Much appreciation also goes to my friends and the department faculty and staff for making my time at Texas A&M University a great experience.

Thanks also to the Department of Homeland Security funded National Center for Foreign Animal and Zoonotic Disease Defense at Texas A&M University and the United States Geological Survey, for support both financially and personally.

I would also like to thank my parents, my elder sister and her family, and my younger brother. They were always supporting me and encouraging me with their best wishes.

Finally, I would like to thank my love, Fang Tang. He was always there cheering me up and stood by me through the good times and bad.

TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

Page

1. INTRODUCTION

1.1 Introduction and Objectives

In the past few years, Avian Influenza (AI) disease has become a topic of concern in many areas of the world. Although the spread of the AI disease is slowing down, the pandemic threat due still exists since the virus is still endemic in some countries. AI is very contagious among birds and some of these viruses can make certain domesticated birds species very sick and kill them, which in turn can cause large economic impacts and raise human health risks.

This dissertation will extend and contribute to current literature in three ways. Specifically,

- Examining whether climate factors are statistically found to be involved in the disease spread and also to produce risk probabilities under climate change
- Examining how media coverage of international AI outbreaks affects meat demand across poultry, beef and pork in the United States
- Examining how AI disease control strategies affect poultry production and welfare under a simulated AI outbreak in the United States

---

This dissertation follows the style of *American Journal of Agricultural Economics.*

Collectively, this dissertation investigates issues surrounding AI outbreaks and livestock related vulnerability. Figure 1-1 shows the underlying linkages among topics in this dissertation.

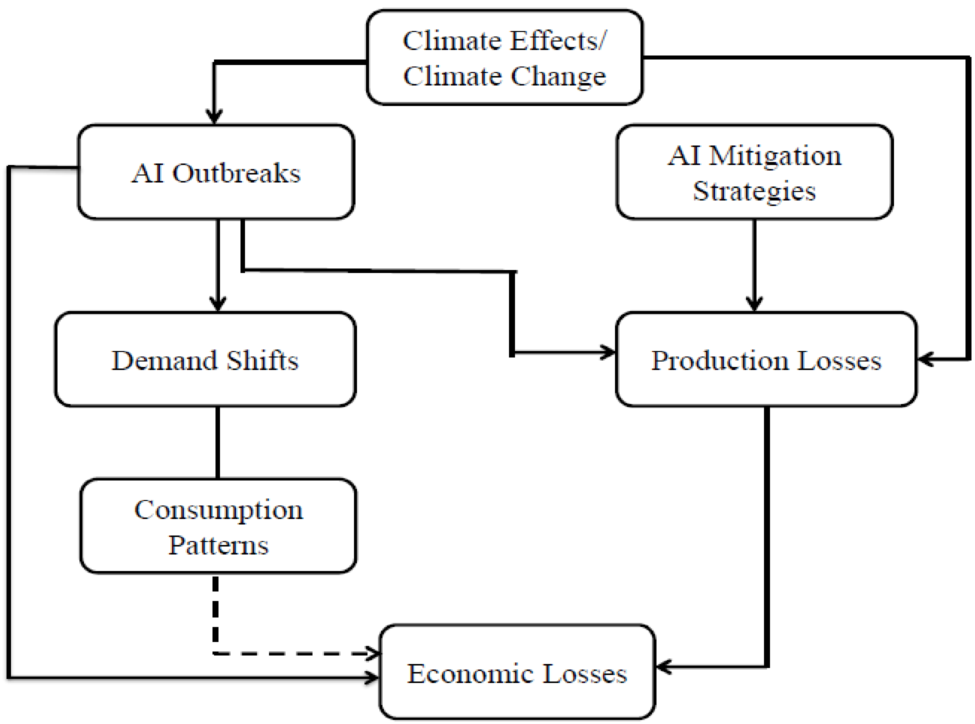


Figure 1-1 Overall Framework of This Study

The dash line indicates the secondary effects of climate change on economic through impacts of AI outbreaks. Arrows point to areas that will be economically/economically examined.

1.2 Plan of Dissertation

This dissertation contains three essays,

- Essay 1 examines the effects of climate factors on the probability and outcomes of AI outbreaks using econometric models, and then simulates the risk of AI outbreaks under past and future changes in climate to evaluate shifts in outbreak probabilities and the associated economic losses
- Essay 2 statistically estimates the economic impacts of international AI outbreak information on meat demand by using a dynamic demand model, which examines both short and long run shocks
- Essay 3 investigates how AI mitigation strategies behave under a simulated AI outbreak. Additional costs caused by past climate change are also evaluated in this essay using results from essay 1

These essays and supporting materials are organized into six sections including,

- Section 1 introduces the problems investigated and the research objectives
- Section 2 provides background information on AI
- Section 3 presents the first essay on climate change and AI outbreaks
- Section 4 presents the second essay on AI media coverage and meat demand
- Section 5 presents the third essay on AI mitigation strategy implications
- Section 6 summarizes contributions, key findings, limitations and directions for future research

2. BACKGROUND OF AI DISEASE

2.1 Background on AI

AI or "bird flu" is a contagious animal disease caused by avian influenza viruses (Cooper et al. 2007; Jin and Mu 2012). Infections can be divided into two low and high extremes of virulence, namely, the highly pathogenic avian influenza (HPAI) and the low pathogenic avian influenza (LPAI). The LPAI is less contagious, and infected species may not carry any symptoms. The HPAI virus spreads rapidly with a high mortality rate among infected birds (up to 90-100% within 48 hours) and can spread to humans[1].

The HPAI H5N1 subtype was initially detected in poultry on a farm of Scotland, UK, in 1959 (Fang et al. 2008). From then until 1990, there were nine H5N1 outbreaks recorded in Europe, North American and Australia. Those outbreaks were contained by stamping out infected flocks (Alexander 2000). From 1990 to 2002, an additional ten H5N1 outbreaks were confirmed (Peiris et al. 2007).

Since 2003, H5N1 outbreaks have occurred at unprecedented levels in terms of scale and geographic distribution, initially through East and Southeast Asia in 2003–2004 and then into Mongolia, southern Russia, the Middle East and to Europe, Africa and South Asia in 2005–2006, with outbreaks recurring in various countries in 2007 (Sims and Brown 2008; Jin and Mu 2012).

[1] More information about avian influenza is available through http://www.cdc.gov/flu/avianflu/. Accessed on March 4, 2012.

As of summer 2010, twelve countries were experiencing an ongoing epidemic of at least one strain AI[2]. Outbreaks of HPAI H5N1 in poultry since 2003 are shown in Figure 2-1.

The H5N1 virus has the ability to cross the species barrier to humans inducing severe disease and even death. The first known human cases were reported in Hong Kong in 1997 and involved deaths of six out of 18 infected persons (Chan 2002; Peiris et al. 2004). The source of human infections appeared to be live-poultry markets where chickens, ducks and geese were sold for human consumption. Figure 2-2 portrays the number of HPAI H5N1 human cases from 2004 to 2012 reported to the World Organization for Animal Health (OIE). To date, the confirmed HPAI cases of human illness and death since 2003 is 596 and 350, respectively[3].

[2] More information is available through http://www.cirad.fr/en/news/all-news-items/articles/2010/science/avian-influenza-the-role-of-migratory-birds. Accessed on March 4, 2012.
[3] More information is available through http://www.who.int/influenza/human_animal_interface/H5N1_cumulative_table_archives/en/index.html. Accessed on March 2012.

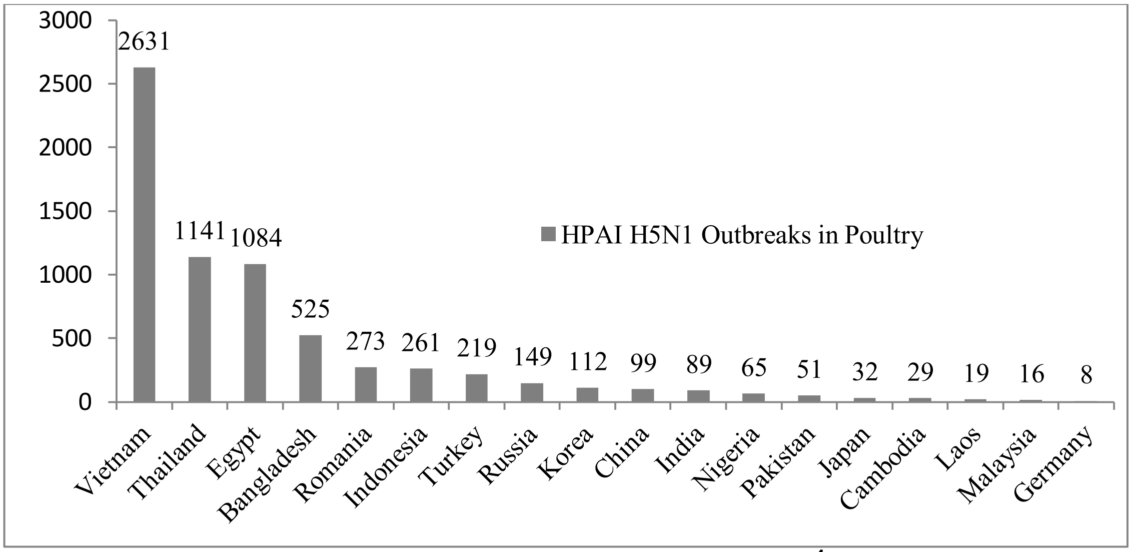


Figure 2-1 Reported H5N1 Outbreaks in Poultry since 2003[4]

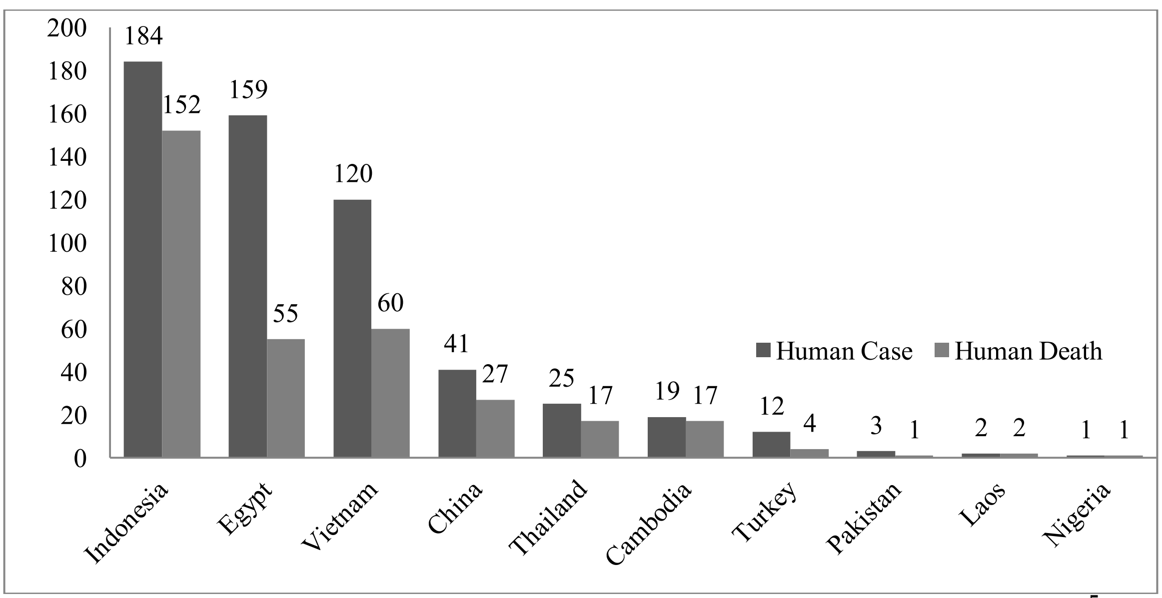


Figure 2-2 Cumulative Number of Human Cases and Death of H5N1 Outbreaks[5]

[4] Available via http://www.oie.int/animal-health-in-the-world/update-on-avian-influenza/2011/, and edited by the author.
[5] More information is available via http://www.cdph.ca.gov/programs/vrdl/Pages/AvianInfluenzaOutbreaksinHumans.aspx, and edited by the author.

2.2 Economic Consequences Caused by AI Outbreaks

AI outbreaks, especially those involving the HPAI strain, pose a significant threat to the economy. Currently the anticipated policy in the event of an HPAI outbreak generally involves mass slaughter of birds. Historically such actions have been seen to reduce aggregate supply of poultry products, causing disruptions in international export markets, and leading to local and national revenue losses (Brahmbhatt 2005; McLeod et al. 2005). As estimated by the World Bank, the global economic impact of a flu pandemic could amount to $800 billion, which is equivalent to 2% of global economic output (Page et al. 2006).

The vulnerability of specific countries has been seen to differ due to the relative importance of their poultry industry plus its structure. In particular, in a country like Vietnam, where the bulk of poultry production is produced by backyard producers, the largest losses fell on small scale commercial chicken producers with limited numbers of other livestock (McLeod et al. 2005). According to Delquigny et al. (2004), the loss of birds, 2.3 months of production and consumption were estimated to have cost $69 to $108 million for households involved in the outbreak. The 2004 HPAI outbreaks in Cambodia caused a significant price reduction (75% drop) for poultry products to producers during the first two months immediately following the outbreaks and prices of other meats rose by 30% as a consequence of the first epidemic wave in 2004(VSF 2004; Otte et al. 2008). In Laos, the total reported losses were only 3% of the national flock, but the impacts were highly localized with nearly 80% of the reported loss in commercial farms in Vientiane province (Rushton et al. 2006).

AI outbreaks also have affected the international poultry market -- a more than $10 billion per annum market (Nicita 2008), likely due to consumers' fear of contacting AI by eating poultry meat (Taha 2007). Observed global poultry exports from the outbreak areas fell by approximately one-third or 6 million tons (CASERED 2004; Basuno et al. 2010). Because of the HPAI outbreaks, Thailand lost its position as the worlds' fifth largest exporter of poultry meat and Brazil replaced China and Thailand as the world's largest supplier of frozen raw chicken products (McLeod et al. 2006; Nicita 2008).

In the United States, several outbreaks were detected during 2003 and 2004. For example, it had H7N2 in New York in 2003, H5N2 in Texas and H7N2 in Delaware, New Jersey, and Maryland in 2004[6]. The largest outbreak of LPAI occurred in 2002, when 4.7 million birds owned by 197 farms were depopulated in Virginia and surrounding states for disease control purpose (Senne 2007). Later, a HPAI strain was diagnosed in Gonzales County, Texas in a flock of infected broiler chickens based on molecular diagnostics in February 2004. In response, 44 countries banned imports on either Texas or U.S.-origin poultry and/or poultry products (Pelzel et al. 2006). The economic losses to the poultry industry in United States due to the closure of export markets following the 2004 HPAI outbreak in Texas were speculated to be as high as hundreds of millions of dollars (Pelzel et al. 2006).

[6] More information on past avian influenza outbreaks is available through http://www.cdc.gov/flu/avian/outbreaks/past.htm.

2.3 Scope of This Study

In this dissertation, I emphasize three aspects of AI outbreaks including risk factors of disease spread, impacts on demand and production in the United States. In the demand side, impacts come from three types of AI information, AI outbreaks in the United States, AI human cases in countries other than the United States and AI news reports covering AI outbreaks all over the world. The spread of AI has received considerable media coverage, which raised fears of consuming poultry meat or related poultry products, in turn having a negative impact on meat demand (Beach and Zhen 2008). It would be interesting to examine how AI outbreak information affects meat demand in the United States since few studies have analyzed this issue so far.

In the production side, poultry producers need to consider the mitigation strategies of animal disease to minimize production costs. There are two disease control options in the AI context, quarantine strategy and vaccination strategy. The former recommends establishing a quarantine strategy zone in a 5-miles radius around the outbreak site within which every flock is depopulated, and then a varying surveillance radius around that zone plus movement restrictions and testing (Pelzel et al. 2006)[7]. The vaccination strategy suggests vaccinating all susceptible flocks in near proximity to the quarantine zone in addition to the quarantine strategy stated above in terms of reducing the probability of infection and the amount of virus produced by an infected flock (FAO 2004). Both strategies depend on the probability of AI outbreaks, the densities of poultry

[7] They portray the zoning strategy actually implemented during the Gonzalez County (East of San Antonio) outbreak in 2004.

flocks and the contact rate between different poultry flocks. In this case, the decision of choosing the quarantine or vaccination response is determined by the expected economic costs due to a potential AI outbreak.

Overall, economic impacts of AI outbreaks are affected by the risk and outcomes of AI outbreaks, which is possibly affected by climate conditions. Thus, it is necessary to examine the spread of AI outbreaks before examining the sequential adverse effects on demand and production. Therefore, this dissertation also dedicates efforts in investigating the relationship between climate and the probability and outcomes of AI outbreaks and then evaluating the associated economic losses of disease outbreaks under past and projected climate change.

3. CLIMATE CHANGE, AI OUTBREAKS AND LOSS

3.1 Introduction

Since 2003, epidemics of the most dangerous AI strain -- HPAI H5N1 -- have occurred with unprecedented frequency across an ever-wider part of the globe. This strain was initially observed in East and Southeast Asia during 2003 and 2004, and migrated to Russia in 2005. Since then, it has spread to the Middle East, Africa and Europe (Alexander 2007; Sims and Brown 2008), and over 60 countries have experienced HPAI H5N1 outbreaks (Alexander 2007). Currently, the list of countries having had HPAI outbreaks is still expanding[8]. HPAI is also a public health concern because this strain is capable of causing human mortality. To date, H5N1 have been reported 596 cases of human infection, resulting in 350 deaths[9].

The global outbreaks of HPAI resulting loss of over 250 million domestic poultry including chickens, ducks, turkeys, quail and ostrich, causing huge negative socioeconomic and livelihood impacts, as well as affecting food and protein resources, wildlife populations and public health (Alexander 2007). Determining the factors involved in HPAI outbreaks spread and producing risk probabilities is important ultimately to target surveillance and control measures, and to reduce losses and improve disease prevention planning (Paul et al. 2010). Climate change is a possible factor in the

[8] More information on current avian influenza outbreaks is available through http://www.cirad.fr/en/news/all-news-items/articles/2010/science/avian-influenza-the-role-of-migratory-birds.

[9] More information is available through http://www.who.int/influenza/human_animal_interface/H5N1_cumulative_table_archives/en/index.html.

widening spread as it may alter conditions involved with disease transmission and persistence including wild bird migration patterns (Si et al. 2009; 2010; Ottaviani et al. 2010) and trade of live poultry (Gilbert et al. 2008; Kilpatrick et al. 2006).

In spite of the importance of forecasting and anticipating the global spread of HPAI outbreaks, few efforts have been made to predict HPAI risk across regions and countries under climate change (Williams et al. 2008). This paper examines the extent to climate is affecting HPAI outbreaks and projects future consequences along with changes in temperature and precipitation. In particular, I examine how temperature, precipitation, seasonality and regional characteristics affect outbreak probability and severity using data from the events in Asia, Europe, Africa and North America. Then I use the estimated statistical results to simulate how much the outbreak probability has shifted and the associated economic loss has involved due to HPAI outbreaks stimulated by past and projected future climate change.

This essay is organized as follows. Section 3.2 reviews previous studies; Section 3.3 presents the statistical models and describes the data; Section 3.4 interprets estimation results; Section 3.5 predicts the risk of HPAI outbreaks under past and future climate change; Section 3.6 evaluates associated economic losses due to HPAI outbreaks under climate change and section 3.7 presents conclusions.

3.2 Literature Review

The literature suggests that climate change may alter several factors involved with HPAI H5N1 spread and persistence. Climate has been found to alter pathogen survival and disease vector behavior. Experimental evidence shows that low temperature and high relative humidity conditions increase the persistence and stability of the HPAI H5N1 virus (European Food Safety Authority 2006; Liu et al. 2007), and climate change would almost certainly influence the HPAI H5N1 virus transmission cycle, and directly affect virus survival outside the host (Gilbert et al. 2008).

Empirical studies including precipitation and temperature indicate lower levels of moisture and humidity may affect wild bird food availability and thereby influence their distributions (Si et al. 2009). Additionally, temperature pattern have been argued to be contributors to an increase in disease occurrence and the spread among live birds (Liu et al. 2007). For example, precipitation was found as an important risk factor affecting the distribution of the H5N1 virus in China (Fang et al. 2008). Cold weather may trigger winter movements of migratory birds and therefore contribute to the spread outside the actual migration period in Europe (Ottaviani et al. 2010; Kilpatrick et al. 2006). A recent study finds that HPAI H5N1 occurrences in wild birds in Europe are highly correlated with increased minimum temperatures and reduced precipitation in January (Si et al. 2010).

In terms of vectors of disease spread, there has been considerable effort investigating how the HPAI H5N1 virus enters previously unaffected countries. The main pathways that have been identified are wild bird migration, live bird trade and the transport of poultry and poultry products. Results from previous studies suggest that wild birds are capable of carrying H5N1virus over long distances and are able to introduce it into new areas during migration (Si et al. 2009; 2010; Gilbert et al. 2008; Kilpatrick et al. 2006; Ward et al. 2009). For example, wild ducks can carry the H5N1 virus asymptomatically (Chen et al. 2005). In addition, circumstantial evidence from Russia and Mongolia indicates that wild birds played a significant role in disease spread, suggesting that they can become infected and travel varying distances before dying (Si et al. 2009; Gilbert et al. 2006; Feare 2007; Cui et al. 2011).

Some studies have attributed the increased frequency of outbreaks to the fast expanding, intensive poultry industry as well as greater movement of live poultry and poultry products (Pfeiffer et al. 2007). Analysis of H5N1 outbreak data in Romania during spring 2006 indicated that the movement of poultry might have facilitated the spread of infection (Ward et al. 2008). However, to quantify the contribution of this pathway is difficult due to the combination of local, unregulated movements and trade in poultry by peasant farmers and the broader-scale, illicit bird trade (Williams et al. 2008; Williams and Peterson 2009). Therefore, few studies have been able to include the dimension of live poultry movements (Kilpatrick et al. 2006).

Studies in Romania, Thailand, Indonesia and China have provided other insights, suggesting that human infection and poultry outbreaks are enhanced by some agro-ecological and socio-demographic factors (Hogerwarf et al. 2010). These factors include agricultural population density, poultry density and local/environmental factors, such as the incidence of rice paddy fields, water sources and transportation. For example, the environment and landscape (specifically the Danube River Delta) played a critical role in the introduction and initial spread of H5N1 in Romania (Ward et al. 2008). The distance to the nearest main city, distance to the nearest body of water and distance to the nearest highway contributed to the spread of the disease in China (Fang et al. 2008). In addition, the risk of HPAI H5N1outbreaks increases if poultry densities (for both chickens and ducks) or road density increase, or areas are located near major cities and highway junctions (Paul et al. 2010; Yupiana et al. 2010).

As discussed above, HPAI outbreaks have received worldwide attention and previous studies have examined factors that may contribute to their risk and spread. However, most have neglected climate factors such as temperature and precipitation, instead focusing on geographic and social-economic characteristics, and few studies have discussed the risk under climate change due to the dynamic pattern of disease outbreaks and the issue of underreporting. In addition, few have addressed the underreporting issues in HPAI outbreaks. This current study extends previous studies in its geographic scope and methodological features and examines

- The effects of climate on the probability and expected numbers of HPAI outbreaks
- The problem of underreporting issues to calibrate the probability of reporting true zeros
- The impacts of climate change on the probability of HPAI outbreaks as realized in the last 20 years and as projected
- The associated economic loss of additional HPAI outbreaks under climate change

Based on previous studies and later estimation models, the relationship between climate change and HPAI outbreaks was constructed, as shown in Figure 3-1.

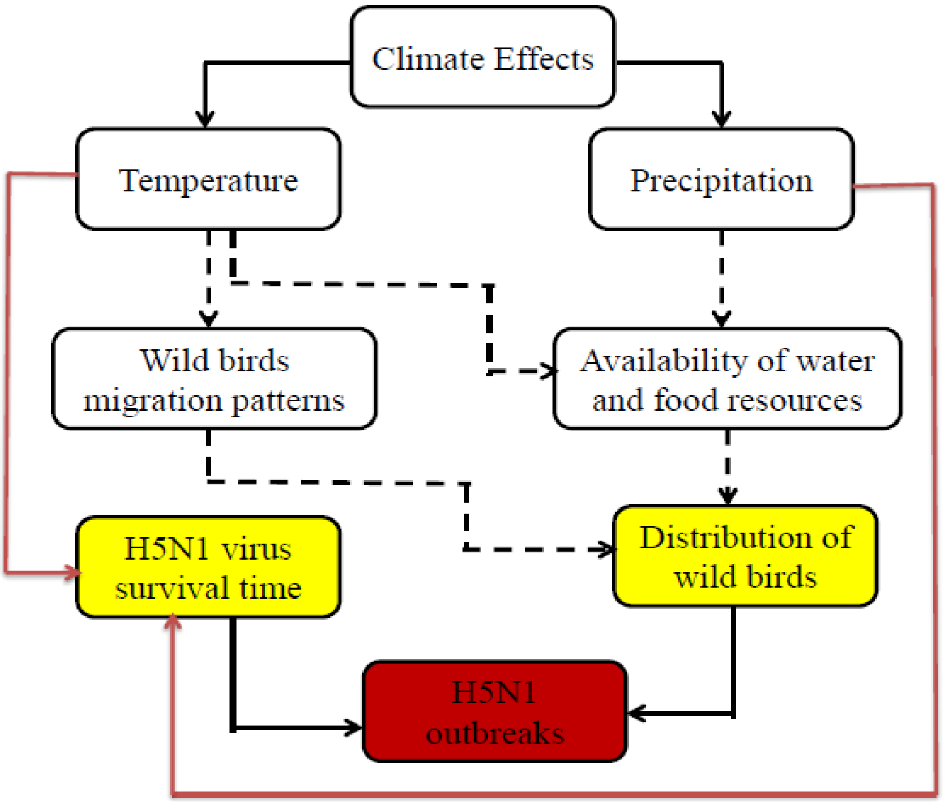


Figure 3-1 Conceptual Framework of Climate Effects on HPAI Outbreaks

Suppose temperature and precipitation are the main climate variables affecting disease outbreaks, impacts could be direct or indirect. Temperature and precipitation could affect the survival and persistence time of HPAI virus directly, for example in the environment and water (Chen et al. 2005; FAO 2004). Temperature and precipitation are also major factors affecting the distribution of wild birds through the availability of food and water to change their migration patterns (Si et al. 2009; 2010; Ottaviani et al. 2010). Therefore, I include a number of other variables

- Proximity of wild bird migratory flyways
- Incidence of extreme cold and hot weather
- Number of live birds traded, and
- Total Gross Domestic Product (GDP)
- Quantity of poultry meat exported
- Density of total population

3.3 Models and Data

The statistical analysis will be carried out over monthly outbreak incidence data cross 90 regions in 16 countries, which are distributed in Asia, Africa, Europe and North America from January 2004 to December 2008. Involved countries are Malaysia, South Korea, Cambodia, Indonesia, Thailand, Japan, Vietnam, China, Egypt, Nigeria, Germany, Romania, Turkey, Pakistan, Russia and the United States, among which China, Egypt, Nigeria, Germany, Turkey and Russia are on major affected flyways according to a recent Food and Agriculture Organization (FAO) fact sheet (Newman et al. 2010). Regions are defined according to each country's size and larger countries have more regions than small couintres. For example, there are 18 regions in China and 9 regions in the United States.

The HPAI outbreak incidence data were drawn from the World Animal Health Information Database (WAHID) Interface for 2005-2008 with 2004 data drawn from the Animal Health Database HANDISTATUS II. The data on total number of confirmed HPAI human deaths by country were drawn from the World Health Organization

(WHO) for the time from January 2004 to December 2008. Three AI outbreak incidence related variables were generated,

- Total count of HPAI outbreaks by region and month
- A dummy variable by region and month where a one indicates whether a region had at least one HPAI outbreak in a given month and zero otherwise
- Total number of confirmed HPAI human death by region and month

Climate data, including mean temperature and total precipitation, were collected from the National Environmental Satellite, Data and Information Service (NESDIS) from January 2004 to December 2008. Mean monthly temperature was computed in Celsius degree (^{o}C), and the total precipitation including rain and/or melted snow was computed in millimeter(mm). Seasonal patterns were also observed, peaking from October to March, when the mean temperature is below 20 ^{o}C and the relative humidity is high (European Food Safety Authority 2006).

Data on country characteristics were also used. I included total GDP from the USDA Economic Research Service (ERS), and the country-to-country trade in live birds was drawn from the Food and Agricultural Organization of the United Nations and the U.S. Census Bureau, Foreign Trade Division. The numbers reported in country-to-country trade in live birds but do not include illegal or unreported trade.

I also used the data regarding commodity code H1-0105 (live poultry, domestic fowls, ducks, geese, etc.)[10] . For each country, either trade value ($) or net weight (kg) were recorded. I calculated the numbers of live birds by using the median number of birds per kilogram 10.61 for poultry (most traded poultry are small domestic fowl<185g) (Kilpatrick et al. 2006).

I also included a set of dummy variables to indicate the location of a country and a flyway of wild bird migration. Disease clusters have occurred throughout the East Asia-Australian flyway (except Australia) since 2003. In the Central Asian flyway, disease clusters started emerging in July 2005 and waned in October 2005. In the Black Sea-Mediterranean flyway, clusters lasted from December 2005 to March 2006. Finally, clusters appeared in the East Atlantic and East Africa-West Asian flyway in March and April 2006, respectively (Si et al. 2009). Figure 3-2 shows the five major wild bird migratory flyways.

[10] I also considered trade of wild birds by aggregating the totals from three commodity codes: H2-010632 (live birds including parrots, parakeets, macaws and cockatoos), H1-010631 (live birds of prey) and H1-010639 (live birds excluding H1-010632 and H2-010631). However, data are missed so many that it is not apporporiate to be used in analysis.

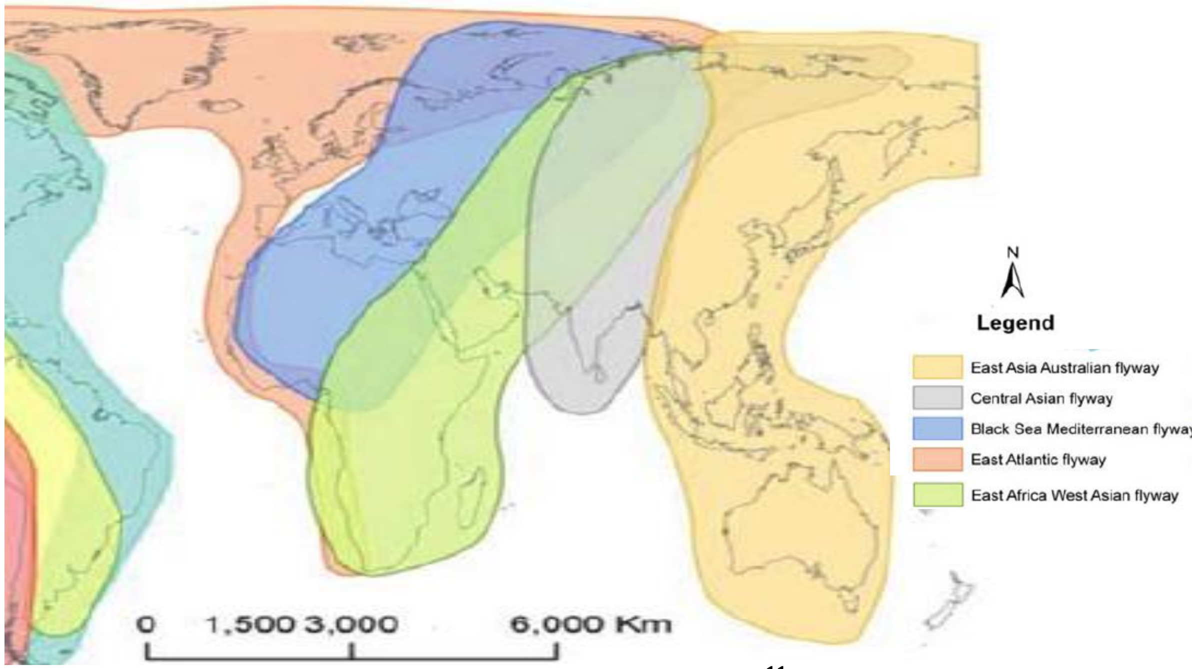


Figure 3-2 Five Broad Flyways of Migratory Wild Birds[11]

Annual data characterizing country characteristics are also used giving GDP, numbers of live poultry traded, population density and quantity of poultry meat exported. Those data are obained for each country from the World Bank, the FAO of the United Nations**,** respectively.

This study focuses on HPAI outbreaks that occurred from January 2004 to December 2008, which captures a peak period of the HPAI epidemic activity in Southeast and Central Asia, Africa and Europe. Data from the WHO show 7984

[11] This map is originally from Si et al. (2009), but is modified by the author.

outbreaks in poultry flocks in almost 60 countries. Table 3-1 provides definitions and statistic descriptions for the variables.

Table 3-1 Definitions and Statistic Descriptions of Variables

Variable	Definition	Mean	Std. Dev.	Min	Max
AIProb	Outbreak incidence in a country and month equaling 1 if outbreaks occured,0 otherwise	0.12	0.32	0	1
$AIProb_{t-1}$	Lagged outbreak incidence	0.12	0.33	0	1
sptemp	Spring* Mean temperature	4.51	8.91	-7.2	34.33
sptemp_sq	Spring*Squared mean temperature	99.65	228.44	0	1178.8
ftemp	Fall* Mean temperature	4.85	9.36	-7.9	35.69
ftemp_sq	Fall*Squared mean temperature	111.05	239.89	0	1273.5
wtemp	Winter* Mean temperature	2.43	7.25	-21	30.40
wtemp_sq	Winter*Squared mean temperature	58.49	171.81	0	924.16
spprecp	Spring* Total precipitation	17.50	58.86	0	2335.8
spprecp_sq	Spring* Squared total precipitation	3770.4	76031.1	0	5455887
fprecp	Fall* Total precipitation	18.90	62.07	0	1143
fprecp_sq	Fall* Squared total precipitation	4208.9	31056.2	0	1306449
wprecp	Winter* Total precipitation	11.45	48.23	0	2383.5
wprecp_sq	Winter*Squared total precipitation	2456.8	77989.3	0	5681244
Cold_Month (index1)	Dummy variable for whether The month average temperature is <= 4^{o}C	0.12	0.32	0	1
Hot_Month (index2)	Dummy variable for whether the month average temperature is >= 28^{o}C	0.16	0.36	0	1

Table 3-1 Continued

Variable	Definition	Mean	Std. Dev.	Min	Max
lnimportp	Logged numbers of live poultry traded	8.95	5.06	0	15.91
lngdp	Logged GDP in billion $	6.40	1.74	1.6	9.49
lnexport	Logged poultry export quantities	10.11	7.27	0	18.88
lnppden	Logged population	4.68	0.91	2.2	6.18
aihuman	Numbers of confirmed AI human death	3.92	8.19	0	45
EAAFW	The East Asia Australian Flyway	0.53	0.50	0	1
CAFW	The Central Asian Flyway	0.12	0.33	0	1
BSMFW	The Black Sea Mediterranean Flyway	0.30	0.46	0	1
EAFW	The East Atlantic Flyway	0.09	0.28	0	1
EFWAFW	The East African West Asian Flyway	0.04	0.21	0	1
Numbers of observations		5400			

Figure 3-3 shows the spatial distribution of HPAI H5N1 outbreaks reported to the World Organization for Animal Health (OIE) since 2005, suggesting that there exists heterogeneity across regions with 12% of regions having had at least one HPAI H5N1 outbreak in the past 5 years.

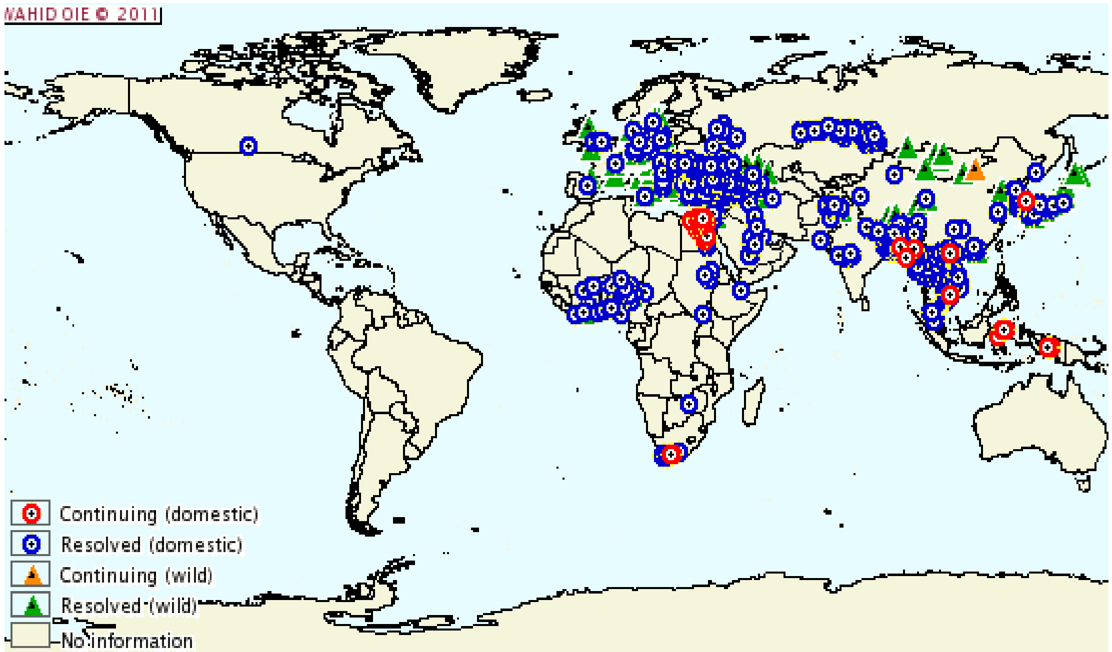


Figure 3-3 Outbreaks of HPAI H5N1 in Poultry since 2005[12]

3.3.1 Functional Form and Variables

We consider the following latent variable model

(3.1) $y_i^* = f(x_i\beta) + u_i$

where y_i^* is the unobserved probability of HPAI outbreaks or counts of HPAI outbreaks;

u_i is a continuously distributed residual, assumed independent of x_i with $u_i \sim N(0,1)$;

x_i is a set of independent variables including:

---

[12] Available via http://web.oie.int/wahis/public.php?selected_start_day=1&selected_start_month=1&selected_start_year=2005&selected_end_day=31&selected_end_month=12&selected_end_year=2011&page=disease_outbreak_map&date_submit=OK.

- Monthly mean temperature in degrees Celsius (°C), total precipitation in millimeters, and squared precipitation and temperature due to the previous inconsistent results in the literature (Si et al. 2010; Fang et al. 2008; Chen et al. 2005)
- Interaction terms of seasonal indicator variables (with summer as the reference) and climate variables (temperature and precipitation): in the northern hemisphere, HPAI infection rates are higher during the spring and fall migration periods (Si et al. 2010; Kilpatrick et al. 2006; European Food Safety Authority 2006), and disease virus might readily persist during spring in cooler areas (Si et al. 2010; Ottaviani et al. 2010)
- Dummies reflecting temperature extremes: HPAI viruses can survive for long periods in the environment, especially when temperatures are low (Fang et al. 2008). In two studies, HPAI virus retained its infectivity at 4°C for more than 100 days but lost its infectivity after 24 hours when kept at room temperature (28°C) (Brown et al. 2007; Shahid et al. 2009). Therefore, two temperature indices are constructed. Cold_Month is 1 when the mean temperature is lower than 4°C, and zero otherwise; Hot_Month is 1 when the mean temperature is higher than 28°C and zero otherwise
- A set of migratory bird flyway indicators that identify indicate (one) whether a country is on one of five specific wild bird migratory flyways, or zero otherwise.

- Variables that give country characteristics include total GDP, poultry export, population density, and country-to-country trade in live poultry as identified and measured by Kilpatrick et al. (2006)

3.3.2 Estimation Approach

The outbreak data to be estimated give a probaility of an outbreak that falls between zero and one or is a count of the number of outbreaks. Estimating an equation for such data requires an approach that takes that into account the characteristics of the data, which usually need regression models for categorical dependent variables (Cameron and Trivedi 1998; Cameron and Trivedi 2009). Specifically, a binary choice or a count outcome model is used depending on whether the dependent variable is a dummy indicator or a count outcome.

3.3.2.1 The dynamic panel binary choice model

I will estimate a relationship between the probability of HPAI outbreaks and a number of regional climate factors, economic characteristics plus the lagged indicator of outbreaks. This is done using the basic functional form[13],

$$(3.2) \quad y_{it}^{*} = x_{it}\beta + \rho y_{i,t-1} + c_i + e_{it}$$

where y_{it}^{*} is the probability of HPAI outbreaks; x_{it} is a vector of independent, contemporaneous explanatory variables; $y_{i,t-1}$ is the lagged dependent variable allowing the current outbreak probability to be altered by whether the region has incurred

[13] The dynamic nonlinear model is used because we are interested in whether there is pure state dependence, that is, $\rho \neq 0$ in the equation after controlling for the unobserved heterogeneity c_i (Wooldridge 2002). In this paper, I am interested to see whether the past HPAI outbreaks could affect the probability of current outbreaks after controlling unobserved effects.

previous ones; c_i is the unobserved effect and is allowed to be correlated with some elements of x_{it} ;and e_{it} is an error term and $e_{it} \mid (x_i, y_{i,t-1},..., y_{i1}, c_i) \sim Normal(0,1)$.

In estimation, y_{it}^* is a latent dependent variable measuring the probability of observed data. Instead of observing y_{it}^*, we observe only a binary variable y indicating whether an outbreak occurred,

$$(3.3) \qquad y_{it} = \begin{cases} 1 & \text{if } y_{it}^* > 0 \\ 0 & \text{if } y_{it}^* = 0 \end{cases}$$

where y_{it} indicates whether a region i had any HPAI outbreaks in time period t.

Without loss of generality, I can reorder the observations starting at $t = 0$, so that y_{i0} is the first observation on y. For $t = 1, 2, ...T$, the density function of y_{it} then can be written as,

$$(3.4) \qquad f(y_1,..., y_T \mid y_0, x, c, \beta) = \prod_{t=1}^{T} \Phi(x_{it}\beta + \rho y_{i,t-1} + c_i)^{y_{it}} [1 - \Phi(x_{it}\beta + \rho y_{i,t-1} + c_i)]^{1-y_{it}}$$

However, to estimate β and ρ consistently, I need to address the initial conditions problem by making an additional assumption on c_i, that is, a decision on how to treat the initial observations y_{i0}. Under the assumption of $c_i \mid (y_{i0}, x_i) \sim Normal(\zeta_0 + \zeta_1 y_{i0} + x_i \zeta, \sigma_a^2)$ (Wooldridge 2000; 2005; 2002), I can specify the density in such a way that can be estimated using the standard Random-Effects Probit Estimation[14],

(3.5) $c_i = \zeta_0 + \zeta_1 y_{i0} + x_i \zeta + a_i$

where $a_i \mid (y_{i0}, x_i) \sim Normal(0, \sigma_a^2)$ which is assumed not to depend on x_{it}.

To avoid a large dimension problem in estimation[15], I use $\bar{x}_i$ to replace x_{it} (Chamberlain 1980), which is the average of x_{it} over time. Also to identify time indicators, which do not vary across i, they must be omitted from $\bar{x}_i$ by setting $\zeta = 0$. In turn, the dynamic Probit model with unobserved effects arises,

$$\begin{aligned} P(y_{it} = 1 \mid x_{it}) &= \Phi[(\zeta_0 + x_{it}\beta + \rho y_{i,t-1} + \zeta_1 y_{i0} + \bar{x}_i \zeta) \cdot (1+\sigma_a^2)^{-1/2}] \\ &= \Phi[(\zeta_{0a} + x_{it}\beta_a + \rho_a y_{i,t-1} + \zeta_{a1} y_{i0} + \bar{x}_i \zeta_a) \end{aligned} \quad \text{for } t = 1, 2, \ldots T \tag{3.6}$$

where the a subscript means that a parameter vector has been multiplied by $(1+\sigma_a^2)^{-1/2}$. This functional form will be used to estimate the HPAI outbreaks. If applying the econometric model to the data, the empirical model for estimation is,

[14] This model is different from the pure random-effects model since we allow some kind of correlation between the error term and independent variables by specifying the conditional distribution of the unobserved effects.

[15] Since I have monthly data from January 2004 to December 2008, x_i is a $k \cdot 60$ matrix if x_{it} is a $n \cdot k$ matrix, which is too large to be estimated based on our sample size.

$$
\begin{aligned}
(3.7)\qquad P(\text{AIProb}_{it}=1\,|\,x_{it}) = \Phi(\bullet) = \Phi(&\zeta_{0a}+\rho_a \text{AIProb}_{i,t-1}+\sum_{s=1}^{3}\beta_{1as} season_{is,t} * precip_{it} \\
&+\sum_{s=1}^{3}\beta_{2as} season_{is,t} * precip\_sq_{it}+\sum_{s=1}^{3}\beta_{3as} season_{is,t} * temp_{it} \\
&+\sum_{s=1}^{3}\beta_{4as} season_{is,t} * temp\_sq_{it}+\sum\nolimits_{j=1}^{2}\beta_{5aj} index_{ij,t} \\
&+\beta_{6a}\,\text{I}npimport_{it}+\beta_{7a}\ln gdp_{it}+\sum\nolimits_{p=1}^{5}\beta_{8ap} Flyway_{ip,t} \\
&+\zeta_{1a} y_{i0}+\sum_{s=1}^{4}\zeta_{2as}\overline{season_{is}\cdot precip_i}+\sum_{s=1}^{4}\zeta_{3as}\overline{season_{is}\cdot precip\_sq_i} \\
&+\sum_{s=1}^{4}\zeta_{4as}\overline{season_{is}\cdot temp_i}+\sum_{s=1}^{4}\zeta_{5as}\overline{season_{is}\cdot temp\_sq_i} \\
&+\sum\nolimits_{m=1}^{2}\zeta_{6am}\overline{index_i}+\zeta_{7a}\overline{\text{I}npimport}_i+\zeta_{8a}\ln\overline{gdp}_i)
\end{aligned}
$$

I can consistently estimate $\zeta_{0a},\beta_a,\rho_a,\zeta_{1a}$ and ζ_a by calculating the conditional Maximum likelihood Method (MLE) and using a Probit regression with random-effects(Wooldridge 2005). The average partial effects can be calculated by using the average across i of $\hat{\beta}_{aj}\phi(\hat{\zeta}_{0a}+x_{it}\hat{\beta}_a+\hat{\rho}_a y_{i,t-1}+\hat{\zeta}_{1a}y_{i0}+\bar{x}_i\hat{\zeta}_a)$ for continuous variables and taking the difference of values at two different x_{jt} for discrete variables, i.e.

$$
\begin{aligned}
&\Phi(\hat{\zeta}_{0a}+x_{-j,it}\hat{\beta}_{a,-j}+\hat{\beta}_{a,j}+\hat{\rho}_a y_{i,t-1}+\hat{\zeta}_{1a}y_{i0}+\bar{x}_i\hat{\zeta}_a) \\
&-\Phi(\hat{\zeta}_{0a}+x_{-j,it}\hat{\beta}_{a,-j}+\hat{\rho}_a y_{i,t-1}+\hat{\zeta}_{1a}y_{i0}+\bar{x}_i\hat{\zeta}_a)
\end{aligned}.
$$

However, if there exists interaction terms in the nonlinear estimation, the marginal effects would be different from the case of calculating the average partial effects of a single variable. In this study, I use interaction terms of seasonal dummies and climate variables, so I employ the marginal effect calculation approaches proposed in Ai and Norton (2003) and Norton et al. (2004).

Suppose one continuous variable x_1 and one indicator variable x_2 interact, the interaction effect is the discrete difference of the single derivative (Ai and Norton 2003; Norton et al. 2004). The marginal effects for climate interaction terms are computed as,

$$\frac{\Delta \frac{\partial \Phi(\bullet)}{\partial x_1}}{\Delta x_2} = \frac{\Delta\{\beta_1 x_2 \phi(\bullet)\}}{\Delta x_2} = \{\beta_1 \phi(\bullet)\}|_{x_2=1}.$$

3.3.2.2 The standard count outcome models

When y_i is the number of outbreaks, normally, a Poisson model is used to estimate these kind of data. Usually, the Poisson distribution is give as,

$$\text{(3.8)} \quad \Pr(Y = y) = \frac{\exp(-\lambda)\lambda^y}{y!} \text{ for } y = 0,1,2,...$$

where y is the observed count and λ is sole parameter determining the distribution with $\lambda > 0$. The expected mean and variance of the Poisson distribution is $E(y_i \,|\, x_i) = \lambda_i = Var(y_i \,|\, x_i)$, which means the conditional mean of each count dependent variable equals to its corresponding conditional variance.

Given the independent observations with the density function, the log-likelihood function of the Poisson distribution for i^{th} observation is calculated as,

$$\text{(3.9)} \quad LL_P = \sum_{i=1}^{n} [-\lambda_i + y_i \log(\lambda_i) - \log(y_i !)]$$

However, in empirical studies, the conditional variance usually exceeds the conditional mean, thereby presenting a problem of over-dispersion. The over-dispersion problem is mainly related to the heterogeneity and positive contagion in data (Bilgic and

Florkowski 2007). As suggested by Cameron and Trivedi (1998) and Cameron and Trivedi (2009), the popularity of the Negative Binomial (NB) model is due largely to its ability to model count data with varying degrees of overdispersion (Lloyd-Smith 2007).Therefore, I first estimate the count outcome using the NB distribution, which is given by,

$$(3.10)\quad P(Y=y)=\frac{\Gamma(\alpha^{-1}+y)}{y!\Gamma(\alpha^{-1})}(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda})^{\alpha^{-1}}(\frac{\lambda}{\lambda+\alpha^{-1}})^{y}, y=0,1,...;\lambda,\alpha^{-1}>0$$

where $E(y_i \mid x_i)=\lambda_i$ and $Var(y_i \mid x_i)=\lambda_i+\frac{\lambda_i^2}{\alpha^{-1}}>E(y_i \mid x_i)$. α^{-1} is a shape parameter which quantifies the amount of overdispersion with $\alpha^{-1}=0$ indicating a standard Poisson model is preferred; x_i are vectors of independent variables pertaining to i observations, and y is the response variable of disease outcomes -- the number of HPAI outbreaks.

Given the probability function, the log likelihood for i^{th} observation is,

$$(3.11)\quad LL_{NB}=\alpha^{-1}\log(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda})+y_i\log(\frac{\lambda}{\lambda+\alpha^{-1}})+\log(\frac{\Gamma(\alpha^{-1}+y_i)}{\Gamma(\alpha^{-1})})-\log(y_i!)$$

3.3.2.3 The mixtural count outcome models

In previous session, the NB model is used to improve the overdispersion problem in the Poisson model by increasing the conditional variance without changing the conditional mean (Long and Freese 2006). However, there is another problem that raises a challenge to the estimation -- the large percent zero observations in the empirical data. When counting outbreaks of infectious diseases, such as AI, these datasets necessarily are drawn from successful outbreaks. Therefore, there is the possibility of selection bias for an increased proportion of exceptionally infectious individuals (Donnelly et al. 2004; Lloyd-Smith 2007). For example, some countries elect not to report AI outbreak cases, to delay reporting them, or to deliberately under-report the serious cases of AI (such as H5N1) due to financial, economic or social reasons (Nature editorial 2006). This is a typical issue in some developing countries, especially for those in Asia and Africa, they selected not to report AI outbreak cases, probably because

- Their financial support for compensation is insufficient due to low GDP and high proportion of chicken production. According to OIE, the major reason is that the compensation for lost chickens is very low (Nordqvist 2006)
- Most of them have had human infectious and human death, therefore, reporting additional outbreaks could breakdown people's belief in disease control and prevention plans, which in turn will cause large panic

In any way, no-reporting or underreporting of AI outbreaks could induce a selection bias problem in the sample since it represents a potential source of uncertainty and error (Li et al. 2008), and it may cause results from the standard apporach underestimated. Thus, it is important to determine which factors could affect the probability of no-reporting or underreporting to get more efficient disease surveillance and control plans if the real probability of outbreaks is higher than that is recorded.

Since it is impossible to observe whether a zero comes from underreporting (sampling zeros which occur by chance) or a true zero observation (structural zeros which are inevitable) (Mohri and Roark 2005), Cameron and Trivedi (2009) recommend assigning a probability for each of the two ways that a zero could arise and estimating a mixed model over the probabilities.

In this study, zeros may come from two ways,

- Channel 1: Countries in Asia and Africa were under-reporting or delay-reporting incidences of AI outbreaks, thus extra zeros were generated, or
- Channel 2: Countries were with a very low frequency of having HPAI outbreaks in past years, thus the probability of true zero outbreaks is high

Because of the specific data generating process, which is unobservable, I could assign a probability for each process and estimate a mixture model with probabilities. As suggested by Ridout et al. (1998), the Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) are both considered here.

If assume that the probability of reporting an extra zero is p and it is determined by a logistic model assuming that the error term follows a logistic distribution. If the standard count distribution is a Poisson, the probability function of the ZIP model is written as,

$$(3.12) \quad P(Y = y_i) = \begin{cases} p + (1-p)\exp(-\lambda), & y_i = 0 \\ (1-p)\dfrac{\exp(-\lambda)\lambda^{y_i}}{y_i!}, & y_i = 1, 2, \ldots \end{cases}$$

The mean and variance of the ZIP distribution are $E(y_i \mid x_i) = (1-p_i)\lambda_i$ and $Var(y_i \mid x_i) = E(y_i \mid x_i)(1+\lambda_i p_i) > E(y_i \mid x_i)$, respectively.

Alternatively, if the standard count distribution follows a Negative Binomial distribution, then a ZINB model is given by,

$$(3.13)\quad P(Y=y_i)=\begin{cases} p+(1-p)(\dfrac{\alpha^{-1}}{\alpha^{-1}+\lambda})^{\alpha^{-1}}, & y_i=0 \\ (1-p)\dfrac{\Gamma(\alpha^{-1}+y)}{y_i!\Gamma(\alpha^{-1})}(\dfrac{\alpha^{-1}}{\alpha^{-1}+\lambda})^{\alpha^{-1}}(\dfrac{\lambda}{\lambda+\alpha^{-1}})^{y_i}, & y_i=1,2,... \end{cases}$$

The mean and variance of the ZINB distribution are $E(y_i \mid x_i)=(1-p_i)\lambda_i$ and $Var(y_i \mid x_i)=E(y_i \mid x_i)[1+1+\lambda_i(p+\alpha)]>E(y_i \mid x_i)$, respectively.

Following Hu et al. (2011), the Poisson, NB, ZIP and ZINB models relate λ to covariates by assuming,

$$(3.14)\quad \lambda_i=\exp(x_i^{'}\delta)$$

In addition, the ZIP and ZINB models relate p to covariates by assuming,

$$(3.15)\quad p_i=\frac{\exp(z_i^{'}\gamma)}{1+\exp(z_i^{'}\gamma)}$$

where x_i are vectors of independent variables affecting the expected numbers of AI outbreaks; z_i are vectors of independent variables affecting the probability of reporting extra zeros, δ and γ are the corresponding vectors of regression coefficients in two processes, respectively.

In order to fit the zero-inflated distributions, the log-likelihood function of ZIP and ZINB for i^{th} observation are calculated as follows, respectively

$$(3.16)\quad LL_{ZIP}=\sum_{i=1}^{n}\begin{bmatrix} I(y_i=0)\log[p+(1-p)\exp(-\lambda)]+ \\ I(y_i>0)[\log(1-p)+\log(\dfrac{\exp(-\lambda)\lambda^{y_i}}{y_i!})] \end{bmatrix}$$

$$(3.17)\quad LL_{ZINB}=\sum_{i=1}^{n}\left[\begin{array}{l} I(y_i=0)\log[p+(1-p)(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda})^{\alpha^{-1}}]+ \\ I(y_i>0)[\log(1-p)+\log(\frac{\Gamma(\alpha^{-1}+y)}{y!\Gamma(\alpha^{-1})}(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda})^{\alpha^{-1}}(\frac{\lambda}{\lambda+\alpha^{-1}})^{y})] \end{array}\right.$$

In both cases, δ and γ are parameters to be estimated. Maximum Likelihood Estimation (MLE) method is used to improve the efficiency of estimation (Wooldridge 2002).

3.4 Estimation Results

Estimation results involving estimated coefficients, predicted outbreak probabilities and expected outcomes of HPAI disease are reported in this section.

3.4.1 The Probability of HPAI Outbreaks

The estimated coefficients from the Probit model with Random-Effects are reported in Table 3-2. To compare, I report results from the full model and alternatives that drop economic variables and indices of migratory flyways, respectively[16] to check which model performs the best.

[16] I also tested the robustness by comparing with the linear probability model with the random-effect model. For most significant variables, these two models give similar results. However, the linear probability model is poor in fitting the data because the within sample mean squared error is much smaller. Therefore, I use results from the Probit model in the following analysis. Estimation results of the linear probability model are available upon request.

Table 3-2 Estimation Results from Regression Models

Variable	Model1	Model2	Model3
$AIProb_{t-1}$	1.4519***	1.4547***	1.4597***
	(0.0665)	(0.0662)	(0.0667)
wtemp	0.0110	0.0103	0.0103
	(0.0124)	(0.0124)	(0.0124)
wtemp_sq	-0.0006	-0.0005	-0.0005
	(0.0005)	(0.0005)	(0.0005)
sptemp	0.0348**	0.0347**	0.0355**
	(0.0174)	(0.0172)	(0.0173)
sptemp_sq	-0.0013**	-0.0013**	-0.0013**
	(0.0006)	(0.0006)	(0.0006)
ftemp	0.0299	0.0281	0.0304
	(0.0205)	(0.0205)	(0.0203)
ftemp_sq	-0.0013*	-0.0013*	-0.0014*
	(0.0008)	(0.0008)	(0.0007)
wprecp	0.0065***	0.0063***	0.0065***
	(0.0021)	(0.0021)	(0.0021)
wprecp_sq	-0.0000***	-0.0000**	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
spprecp	0.0004	0.0005	0.0004
	(0.0016)	(0.0016)	(0.0016)
spprecp_sq	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
fprecp	0.0007	0.0008	0.0007
	(0.0011)	(0.0011)	(0.0011)
fprecp_sq	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Cold_Month	0.3559**	0.3590**	0.3507**
	(0.1420)	(0.1418)	(0.1411)
Hot_Month	-0.0618	-0.0654	-0.0540
	(0.0950)	(0.0947)	(0.0948)
lnpimport	0.0479		0.0388
	(0.0828)		(0.0839)
lngdp	-1.0322***		-0.9979***
	(0.3107)		(0.3104)
EAAFW	0.4581**	0.6065***	
	(0.2283)	(0.2222)	
CAFW	0.0911	-0.0515	
	(0.1372)	(0.1216)	

Table 3-2 Continued

Variable	Model1	Model2	Model3
BSM FW	0.5612**	0.8317***	
	(0.2468)	(0.2130)	
EAFW	1.0577***	1.0748***	
	(0.2725)	(0.2760)	
EAWAFW	0.8811***	1.1591	
	(0.3336)	(0.3025)	
Constant	-1.2822	-2.0770**	-0.0965
	(1.0490)	(0.9741)	(0.9734)
sigma_u	0.1171**	0.1318***	0.1702***
	(0.0512)	(0.0483)	(0.0451)
rho	0.0135	0.0171*	0.0282**
	(0.0117)	(0.0123)	(0.0145)
Likelihood-ratio test of rho=0	1.83*	2.80**	6.41***
Brier Score (with-in-sample)	0.0689	0.0691	0.0697
Brier Score (out-of-sample using 2009 data)	0.26	0.26	0.27
Brier Score (out-of-sample using 2010 data)	0.20	0.20	0.22

Note: variable definitions are in Table 3-1; * p<0.1, ** p<0.05, and *** p<0.01; standard errors are in parenthesis; Model 1 is the full model with all variables; Model 2 is the reduced model without economic variables and Model 3 is the reduced model without indices of wild bird migratory flyways.

I find significant nonlinear effects of climate variables on HPAI outbreaks. Model 1 shows that in the spring, outbreak risk increases as temperature rises up to a threshold where it reduces. HPAI outbreak probability peaks at 13^{o}C. Similarly, disease outbreaks increase with more precipitation in winter but peaks when precipitation is around 140 mm.

I present the calculated marginal effects and associated standard errors in Table 3-3. There we see that the total effects of temperature in spring will increases the risk of HPAI outbreaks by 0.0056%. Precipitation also has statistically significant and positive impacts on HPAI outbreaks in winter. Apparently, precipitation affects the risk of disease outbreaks through its effects on the water and food resource and on AI virus survival time. Compared to temperature, precipitation has the larger marginal effect on the risk of 0.13% (model 1).

Table 3-3 Average Partial Effects from Regression Models

Variable	Model1	Model2	Model3
$AIProb_{t-1}$	34.2176***	34.5219***	35.0526***
	(0.0249)	(0.0250)	(0.0252)
sptemp	0.0056**	0.0246**	0.0210**
	(0.0000)	(0.0001)	(0.0001)
ftemp	0.3241	0.0349	0.0006
	(0.0022)	(0.0003)	(0.0000)
wtemp	0.2228	0.2770	0.2542
	(0.0025)	(0.0033)	(0.0031)
spprecp	0.0001	0.0004	0.0002
	(0.0000)	(0.0000)	(0.0000)
fprecp	0.0075	0.0010	0.0000
	(0.0001)	(0.0000)	(0.0000)
wprecp	0.1311***	0.1699***	0.1597***
	(0.0004)	(0.0006)	(0.0005)
Cold_Month	5.0566**	5.1614**	5.1054**
	(0.0241)	(0.0244)	(0.0245)
Hot_Month	-0.6859	-0.7331	-0.6206
	(0.0102)	(0.0103)	(0.0106)
lnpimport	0.5498		0.4592
	(0.0095)		(0.0099)
lngdp	-11.8584***		-11.8137***
	(0.0359)		(0.0370)
EAAFW	5.1908**	6.9549***	
	(0.0253)	(0.0249)	

Table 3-3 Continued

Variable	Model1	Model2	Model3
CAFW	1.1044	-0.5800	
	(0.0175)	(0.0133)	
BSMFW	7.7933*	12.7792***	
	(0.0401)	(0.0400)	
EAFW	22.2110***	22.9077***	
	(0.0827)	(0.0849)	
EAWAFW	17.7875**	26.9119***	
	(0.0976)	(0.1029)	

Note: variable definitions are in Table 3-1; * p<0.1, ** p<0.05, and *** p<0.01; Coefficients are multiplied by 100; standard errors are in parenthesis; Model 1 is the full model with all variables; Model 2 is the reduced model without economic variables and Model 3 is the reduced model without indices of wild bird flyways. Marginal effects of interaction terms are calculated using methods proposed by Ai and Norton (2003) and Norton et al. (2004). corresponding standard errors are adjusted as well.

Previous studies have examined the role of wild bird movements in HPAI spread, and some find that wild birds can carry the virus great distance through their migration flyway (Si et al. 2009). Results from Tables 3-2 and 3-3 also show that whether a country is on the migration flyway is statistically significant and positively related to disease outbreaks. I include five flyways: the East Asia-Australian flyway, the Central Asia flyway, the Black Sea-Mediterranean flyway, the East Atlantic flyway and the East African-West Asian flyway. For those flyways that have statistically significant effects, I find the East Atlantic flyway has the largest effects on disease outbreaks than other three. Previous studies have found that HPAI outbreaks in some European and African countries are very likely due to early movements of wild birds (Si et al. 2010; Ottaviani et al. 2010). My results confirm that wild bird migratory flyway is one of the major factors of disease outbreak and spread, so countries on these flyways should pay more attention to disease control and prevention plans.

I also find the unsurprising result that past outbreaks increase the chance of a current outbreak. A number of Asian countries succeeded in eradicating the disease, notably Japan, Malaysia, and the Republic of Korea, but all of these experienced reincursions of H5N1 virus (Newman et al. 2010). These repeated outbreaks provide a source of virus maintenance once introduced into an area (Sims and Narrod 2008). The dynamics of how HPAI survives is also very important for a country's decision of whether to implement disease prevention and control strategies.

In addition, the probability of disease outbreaks is correlated to a country's total GDP. A higher GDP the country has, a lower risk it faces. It is argued that a country with higher development level, it will implement a more effective surveillance system. For countries, such as China, Viet Nam, Thailand and Nigeria, they had the financial issue of disease compensation and control plan. Sometimes, disease outbreaks could not be reported immediately due to insufficient disease surveillance and reporting system.

3.4.2 Prediction Accuracy Assessment

Although regression results are quite stable across three models in Table 3-2, I use the Brier score (Brier 1950) and Probabilistic graph (Casillas-Olvera and Bessler 2006) to check the forecast performance.

The Brier score reference is a popular measure of forecast accuracy and measures the difference between the actual event and the forecast probabilities. In the context of the dynamic panel Probit model, the overall Brier score is, (3.18) $$BS = \frac{\sum_{t=1}^{T} bs_t}{T} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{N}(\hat{p}_{it} - d_{it})^2}{TN}$$

where BS is the total Brier score, $\hat{p}_{it}$ is the predicted probability of HPAI H5N1 outbreaks and d_{it} is the index of event occurs, in other words, with index equals one of H5N1 outbreak and zero of H5N1 not occurring.

The Brier score is similar to the mean squared error but it ranges from zero (prefect prediction) to one (imperfect prediction). A lower Brier score indicates better predictions. In Table 3-2, I present the Brier scores using within sample prediction as well as out-of-sample forecast using data from 2009-2010. Subsequently, model 1 and model 2 give much smaller scores than model 3 indicating they fit somewhat better; however, it is still difficult to make decision which model is the best.

To resolve this, I draw the probabilistic graph using data from 2009-2010 (Casillas-Olvera and Bessler 2006; Yates 1988). The basic idea is to run a regression of,

(3.19) $$\widehat{p}_{it} = a_{it} + b_{it}d_{it} + e_{it}$$

where a_{it} is the intercept for ith country at time t, b_{it} is the slop and e_{it} is the error term. If event index $d_{it} = 1$, then $p_{it} = a_{it} + b_{it}$; otherwise, $p_{it} = a_{it}$. Therefore, we could plot a two-way graph with event index and the predicted probability and compare it with a 45° line. The area between the regression line and 45° line represents the prediction error with smaller areas indicating better predictions. Figure 3-4 shows the area of prediction error and model 1 is relatively better than model 2. Therefore, I use model 1 in my subsequent predictions.

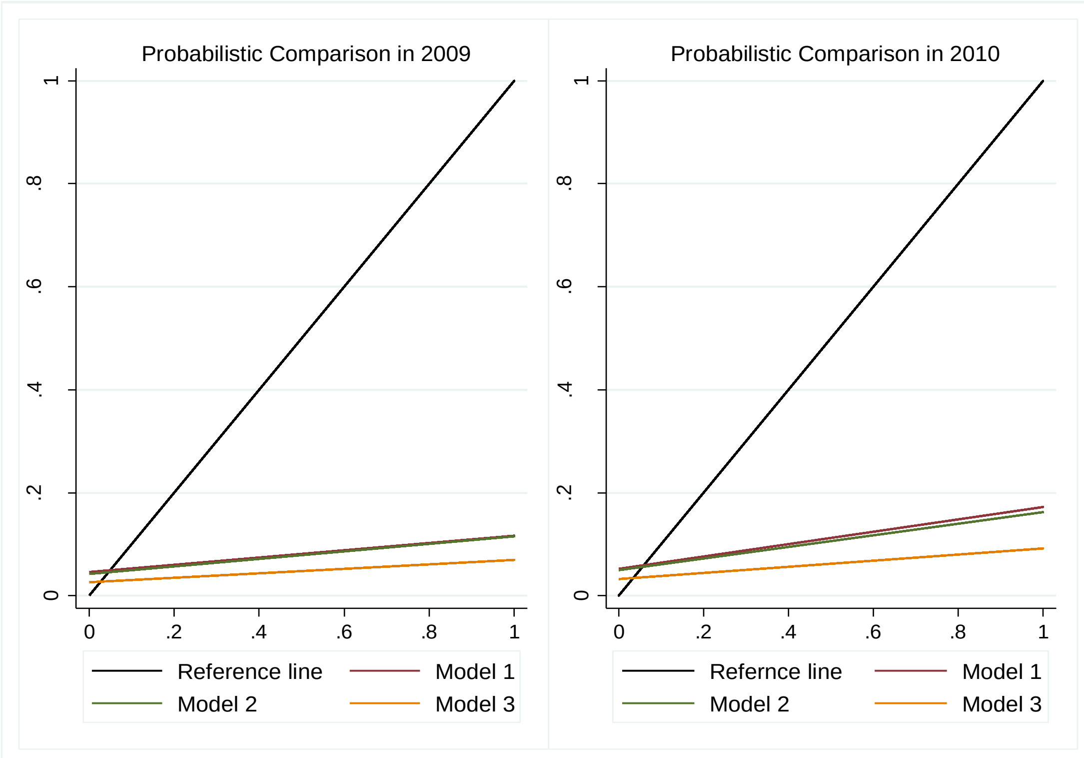


Figure 3-4 Probabilistic Graphs

3.4.3 The Severity of HPAI Outbreaks

Before going to the estimation results of HPAI outbreaks severity, Figure 3-5 shows the distributions of the Poisson, the NB model and the observed outbreaks. It could be seen that Poisson model is over-dispersed and the NB model fits data better.

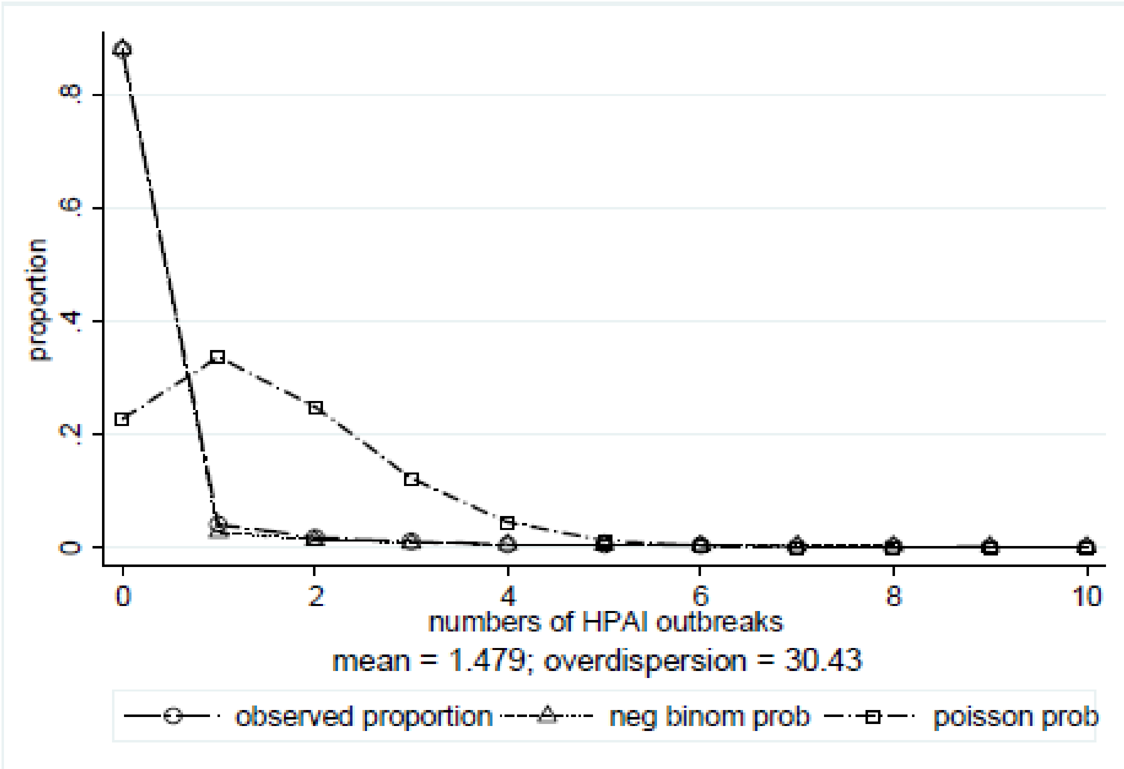


Figure 3-5 Comparison between the Poisson and NB Model

I also compute the Pearson goodness-of-fit to test whether observations are random, whose distribution belongs to a Poisson distribution and the null hypnosis is rejected at the 1% confidence level, which means that results from the Poisson regression may be not appropriate, suggesting the NB model is preferred. I also report results from the ZINB and ZIP model because of the problem of excess zeros. Table 3-4 shows these regression results.

Table 3-4 Regression Results of HPAI Outbreak Outcomes

Variable	NB		ZIP		ZINB
wtemp	0.9544		1.0391		1.0689**
	(0.0336)		(0.0459)		(0.0296)
wtemp2	1.0021		1.0002		0.9987
	(0.0014)		(0.0016)		(0.0012)
sptemp	1.0831		1.1115		1.2259***
	(0.0634)		(0.0983)		(0.0671)
sptemp2	0.9971		0.9965		0.9931***
	(0.0021)		(0.0031)		(0.0020)
ftemp	0.9629		0.9693		1.0720
	(0.0593)		(0.1410)		(0.0783)
ftemp2	1.0006		1.0014		0.9973
	(0.0022)		(0.0055)		(0.0025)
wprecp	1.0235***		1.0024		1.0141***
	(0.0050)		(0.0086)		(0.0054)
wprecp2	0.9999***		1.0000		1.0000***
	(0.0000)		(0.0000)		(0.0000)
spprecp	1.0080**		1.0018		1.0025
	(0.0037)		(0.0033)		(0.0030)
spprecp2	1.0000***		1.0000		1.0000
	(0.0000)		(0.0000)		(0.0000)
fprecp	1.0015		1.0002		1.0004
	(0.0036)		(0.0059)		(0.0031)
fprecp2	1.0000		1.0000		1.0000
	(0.0000)		(0.0000)		(0.0000)
index1	3.5265***		3.2549*		6.3519***
	(1.2821)		(2.1052)		(2.8880)
index2	0.5129**		0.4126		0.5592**
	(0.1560)		(0.2246)		(0.1468)
$AIProb_{t-1}$	32.3001***	0.0824***	4.2514***	0.0247***	9.5719***
	(7.6831)	(0.0138)	(0.8943)	(0.0125)	(2.5009)
lnpimport	0.9677		1.0094		0.9243**
	(0.0266)		(0.0422)		(0.0364)
lngdp	0.4636***	1.3067***	0.7725**	1.1073	0.5724***
	(0.0462)	(0.0600)	(0.0958)	(0.1456)	(0.0881)
EAAFW	0.4874	0.9681	0.2937**	0.5497	0.0093***
	(0.3055)	(0.4019)	(0.1537)	(0.4250)	(0.0132)

Table 3-4 Continued

Variable	NB		ZIP		ZINB
CAFW	3.6155***	0.4837***	0.8386	1.3364	6.4583***
	(1.2610)	(0.0978)	(0.3132)	(0.7756)	(2.4710)
BSMFW	0.3283	0.8754	0.1943***	0.5905	0.0150***
	(0.2274)	(0.3036)	(0.1127)	(0.2677)	(0.0185)
EAFW	3.5945***	0.4562***	1.3049	0.5149	0.4582
	(1.7766)	(0.1164)	(0.4919)	(0.2484)	(0.2736)
EFWAFW	0.5050	0.4501	0.0526***	0.1750	0.0072***
	(0.3964)	(0.2632)	(0.0328)	(0.1887)	(0.0111)
lnexport		1.0275**		1.0870***	
		(0.0115)		(0.0273)	
lnppden		0.7807*		0.7320	
		(0.1030)		(0.1650)	
aihuman		0.9568***		0.6116***	
		(0.0094)		(0.0883)	
N	5271		5271		5271
AIC	6366.88		21727.18		5940.69
BIC	6524.56		21950.56		6170.64
Log-likelihood	-3159.44		-10829.59		-2935.35

Note: [a] Exponentiated coefficient; variable definitions are in Table 3-1; * p<0.1, ** p<0.05 and *** p<0.01; Standard errors in parentheses.

For variables in both binary and count equations in ZIP and ZINB regression, the signs of the corresponding coefficients from the binary regression have opposite direction of those from the count regression. It is because the binary process is prediction of outbreaks that always have zero counts, so a positive coefficient implies lower outbreaks. The count process predicts number of outbreaks so that a negative coefficient would indicate lower outbreaks (Long and Freese 2006).

A country with a higher GDP has a lower probability to report extra zero of HPAI outbreaks, and the probability is about 0.2 less than that for a country with lower

GDP level. This is probably because most countries in this study are developing countries and a big proportion of their GDPs are coming from agriculture production, especially poultry production.

Countries with lower export of poultry products have a smaller probability of reporting extra zeros with a 0.37 difference between the largest and smallest export countries. Taking Thailand and China as examples, they are two of the largest exporters of poultry products in the world market. Reporting HPAI can cause huge economic losses due to drops of domestic consumption or international demand (McLeod et al. 2006; Nicita 2008). Although there is a risk of disease underreporting, countries with lower GDP and higher poultry production would have incentive to keep the information of disease outbreaks unpublished. As animal diseases like HPAI can spread worldwide if the country does not take an action immediately, it is necessary to stimulate countries with lower GDP and higher level of poultry production to inform and report any animal disease outbreak.

A country's decision of underreporting or no reporting is related to its history of HPAI outbreaks or associated human death, both of which will increase the underreporting probability. It is possible that reported disease was not controlled, or even it was repeating or causing human death in some regions. Releasing news of disease outbreaks and spread will challenge people's faith in public policy of and efficiency in disease prevention and control. In addition, if a country has repeated disease outbreaks, it is difficult for this country to convince other countries in the world market that their poultry meat or products are safe. If releasing news of disease outbreaks, this export country probably will lose its advantage in international market.

For factors determining the expected number of HPAI outbreaks, results from NB and ZINB are consistent for most interested variables. For example, winter precipitation has inverted U-shape effects on the expected number of AI outbreaks with outbreaks increase as winter precipitation rises and decrease if precipitation beyond a certain threshold. In addition, if temperature is below $4^{o}C$, it will increase the expected number of AI outbreaks by a factor of 3.53, and 6.35 for NB and ZINB, respectively, holding all other variables constant. Similarly, temperature that is higher than $28^{o}C$ will decrease the expected numbers for NB and ZINB.

If hold other variables constant, countries with higher GDP have a higher probability of reporting zero outbreaks and will have less expected numbers of HPAI outbreaks by a factor of 0.46, 0.77 and 0.57 for NB, ZIP and ZINB model, respectively. Figure 3-6 shows that conditional on reporting, the probability of zero HPAI outbreaks is higher in developed countries than that in developing countries. However, the probability with more than one outbreak in developed countries is much lower than that in low-income countries.

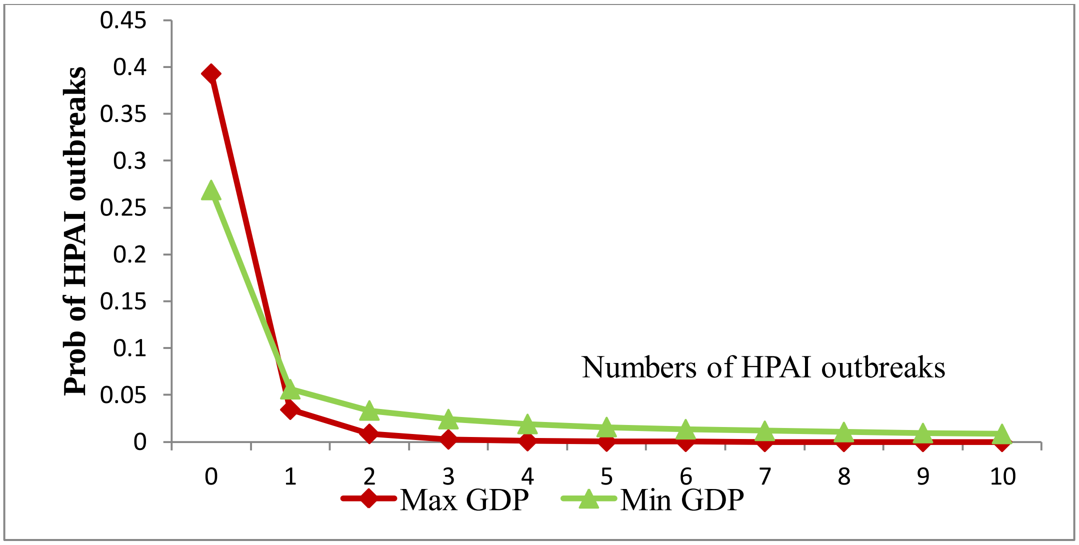


Figure 3-6 Probability in High-income and Low-income Countries

Previous literature found that the number of HPAI outbreaks increases along with more movements of people and lower per capita poultry production in a region where population of people is intensive (Fang et al. 2008; Hogerwarf et al. 2010). Some developed countries have a higher productivity of poultry production and lower density of people population, and in most cases, these countries have larger investments in disease prevention. Therefore, these countries can control disease easily, even with outbreaks.

Whether a country is on the wild bird migration flyways also has significant impacts on the expected number of HPAI outbreaks. Particularly, countries on the Central Asian Flyway will increase the expected disease outbreak numbers. Moreover, a country's expected numbers of AI outbreaks are associated with past AI outbreaks, which will be increased if this country has HPAI outbreaks in the past.

3.4.4 Tests of Model Specification

Table 3-4 also reports statistical criteria of model selection including the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Vaudor et al. 2011), which are given by,

(3.20) $AIC = 2k - 2\ln(L)$

(3.21) $BIC = n\ln(\hat{\sigma}_e^2) + k\ln(n)$

where k is the number of parameters in the statistic model and L is the maximized value of the likelihood function for the estimated model; n is the total observation and $\hat{\sigma}_e^2$ is the error variance for the estimated model.

Among all three models, the ZINB gives the smallest BIC and AIC values, which suggests that the ZINB model fits data the best, followed by NB, while ZIP is the worst. Additionally, the Log-likelihood Ratio (LR) test of NB versus ZINB prefers the ZINB model at the 1% confidence level.

The alternative way to test which model performs better is to compare the difference between predicted and observed values (Long and Freese 2006; Vuong 1989)[17]. According to Long and Freese (2006), the mean predicted probability is given by,

[17] Actually, Long and Freese (2006) developed a package that could be installed in STATA and the name of the code is "*countfit*".

(3.22) $\bar{P}_{predicted}(y=m)=\frac{1}{N}\sum_{i=1}^{N}\widehat{P}(y_i=m\,|\,x_i)$

(3.23) $\Delta\bar{P}(y=m)=\widehat{P}_{observed}(y=m)-\bar{P}_{predicted}(y=m)$

where m is the number of HPAI outbreaks. N is the total observation for estimation and x_i is a set of independent variables affecting the expected number of HPAI outbreaks.

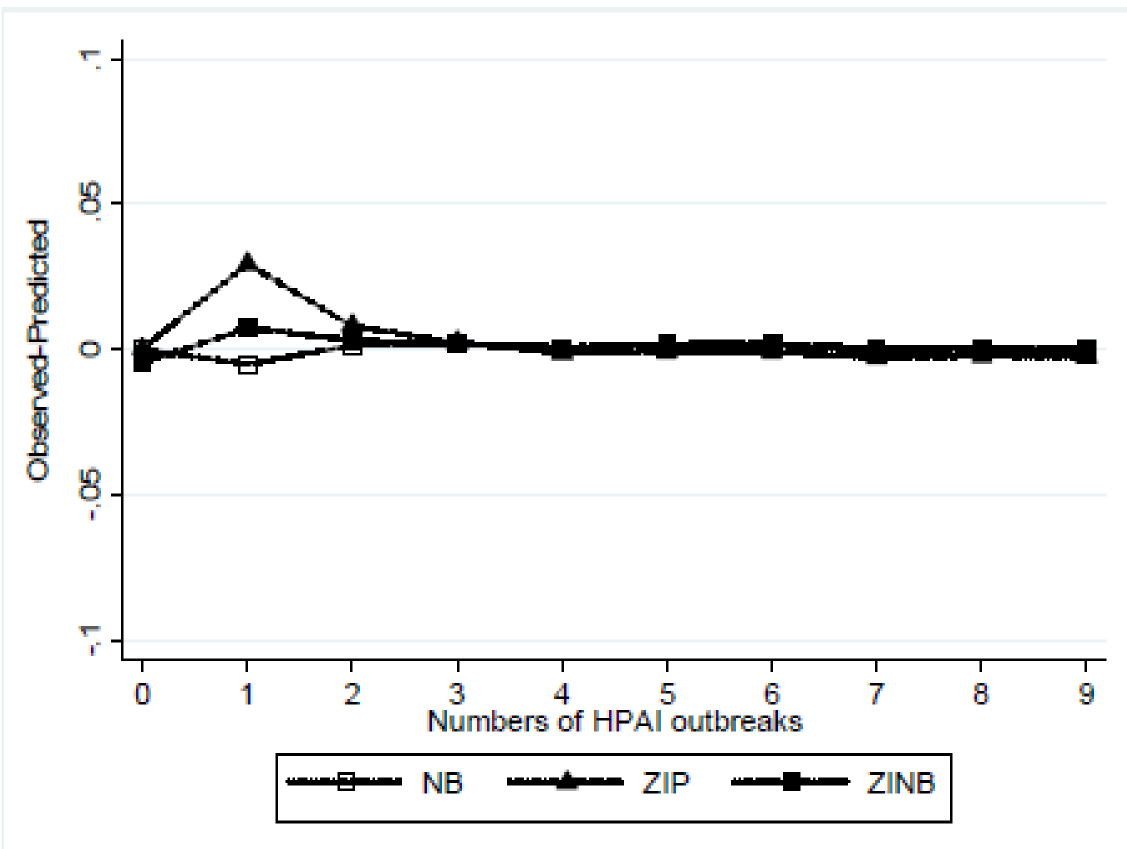


Figure 3-7 Mean Probabilities of Count Regression Models

Figure 3-7 shows the difference of mean probability among three count regression models. Points above zero indicate more observed counts than predicted and points below zero indicate more predicted than observed (Long and Freese 2006). The graph shows that ZIP model has a problem predicting the average numbers of zeros, while NB and ZINB do equally well. However, combining BIC and AIC values as well as the LR test results, the ZINB model is the best for fitting data and therefore, it will be used in following analyses.

3.5 Impacts of Climate Change on Disease Outbreaks

Using results from the full Probit regression model, I predict the effect of climate change on the probability of HPAI outbreaks in each country. In this case, I will discuss and examine

- How much has the realized climate change of the last 20 years contributed to today's outbreaks
- How much will projected climate change of the future 2 decades contribute to the likelihood of future outbreaks

3.5.1 Past Climate Change Contributions to Current Outbreaks

Based on historical records, the Intergovernmental Panel on Climate Change Fourth Assessment Report in 2007 (IPCC AR4) presents data indicating that the global average temperature has increased by 0.55°C per decade from 1970-2006 (IPCC 2007). Changes in overall precipitation amounts vary by regions and seasons, but globally there has been a statistically significant 2 to 4% increase in the frequency of heavy and extreme precipitation events when averaged across the middle and high latitudes during the last three decades of the 20th century (Kunkel 2003; Groisman et al. 2005).

I use the observational climate data used in IPCC AR4 (IPCC 2007), separately from the intervals 1971-1980, 1981-1990 and 1991-2000, and compare it to the current probabilities of outbreaks. Figure 3-8 shows the annual average temperature (°C) and precipitation (mm/month) data for the past 10 and 20 years in each country[18]. Compared with mean temperature and precipitation in the northern hemisphere in 1971-1980, temperature increased in all countries while changes in precipitation vary. As shown in Figure 3-8, Cambodia and South Korea has heavier precipitation as time goes by, whereas Romania, Thailand and Vietnam have less.

Controlling all other variables and using the past temperature and precipitation data, I compute the influence of past versus current climatic conditions on the probability of HPAI outbreaks in the figure in page 56. Other than Indonesia, I find the changes of temperature and precipitation in past 20 years have increased the risk of HPAI outbreaks. In other words, climate change as observed to date has significantly increased the probability of HPAI, which indicates that climate change is one of the forces driving the recent increase in outbreaks observed.

[18] I use the climate in 1971-1980 as the baseline, and calculate the difference of temperature and precipitation between 1971-1980 to 1981-1990 for a 10-year comparison and 1971-1980 to 1991-2000 for a 20-year comparison.

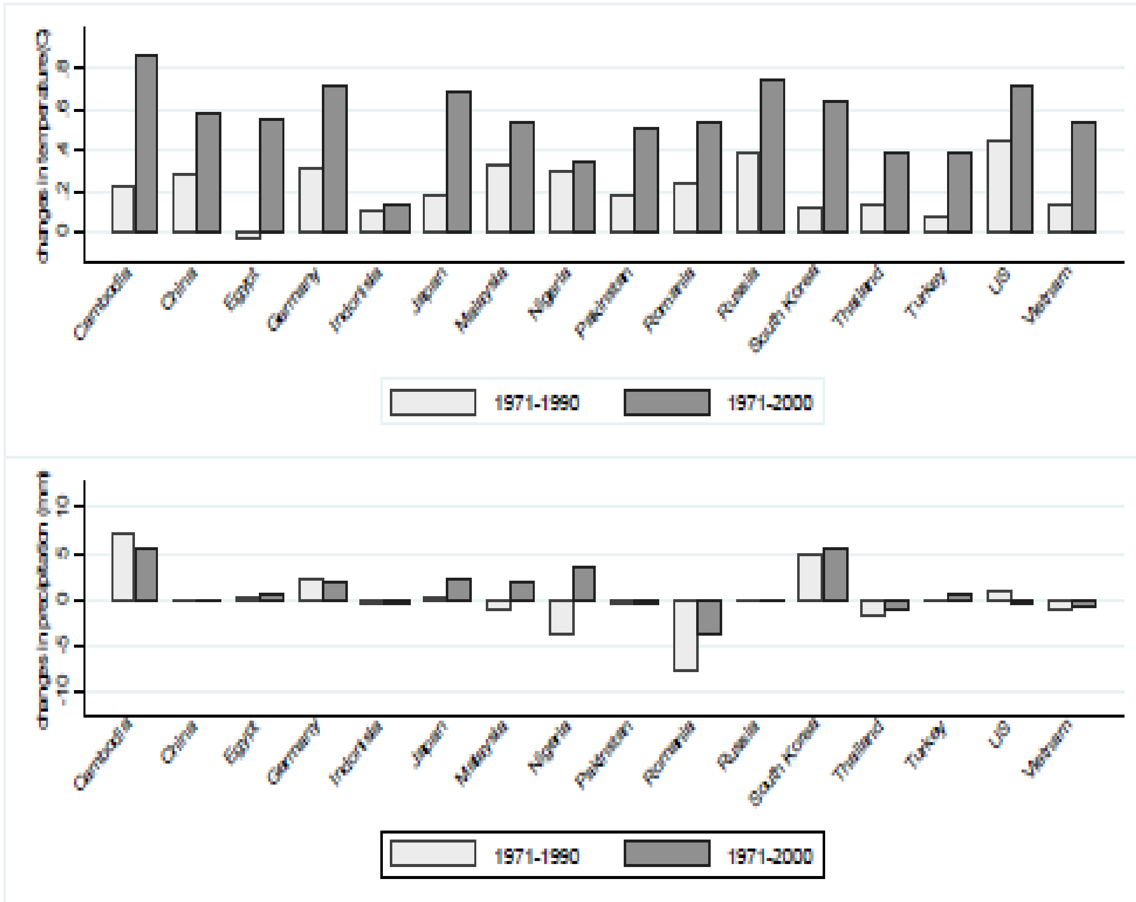


Figure 3-8 Changes in Climate in Past 20 Years[19]

3.5.2 Projected Climate Change Contributions to Future Outbreaks

Now I turn attention to the effects of future projected climate change on outbreak risk. I use projections from three Global Climate Models (GCMs) used in IPCC AR4 (IPCC 2007). The chosen climate models are,

[19] I use the climate in 1971-1980 as the baseline to calculate the difference of temperature and precipitation from 1971-1990 and 1971-2000.

- The Hadley Center coupled model, version 3 (HAD: CM3), which is a stable global mean climate Collins et al. (2001) and is a mid-sensitivity case (Schlenker et al. 2006)
- The Geophysical Fluid Dynamics Laboratory global climate model, version 2.0 (GFDL: CM2.0), which is a model with strikingly lower drifts in hydrographic fields such as temperature and salinity, and more realistic currents that are closer to their observed values (Gnanadesikan et al. 2006; Delworth et al. 2006)
- The Centre National de Recherches Météorologiques coupled atmosphere-ocean climate model, version 3 (CNRM: CM3), which achieves a reasonable simulation of present-day climate and simulates a general increase in precipitation throughout the twenty first century (Salas-Mélia et al. 2005)

There are multiple scenarios run with each climate model. I choose to use those under the A1B emission scenario, a medium scenario relative to the IPCC Special Report on Emission Scenarios (SRES) range (IPCC 2007; Nakićenović 2000). In addition, the simulated warming over a short time period (i.e. by 2030) is not very sensitive to the choice of scenarios across the SRES set (IPCC 2007).

Through the IPCC Data Distribution Center (DDC), I obtained the average of projected temperature and precipitation between 2011 and 2030[20] for each climate model. Considering the uncertainty of projections from each climate model, I use the

[20] I project effects for 2030 to minimize uncertainties in climate change and economic development.

temperature and precipitation, which is averaged over three climate models, and predict the probability of HPAI outbreaks under these climate conditions.

Nearly all projections indicate increased temperature in countries (in Figure 3-9). Even though future climate changes will be highly spatially variable, some model climate projections suggest that precipitation is not uniformly distributed and will increase at high latitudes, and decrease in the tropical and subtropical regions (IPCC 2007). In turn, Figure 3-10 shows the effect on probabilities of HPAI outbreaks under future climate change.

Clearly, projected climate change increases the risk of HPAI outbreaks in most countries. I find big increases in disease outbreak probabilities in Indonesia, Thailand and Vietnam (Note all these countries are in lower latitudes and projections indicate increases in temperature). In addition, these countries have total GDP that is under the world average. For countries located in temperate zone, they will have an increasing or decreasing risk of disease outbreaks depending on local changes in temperature and precipitation. Other countries, such as Japan, South Korea and Russia, have a declining probability of HPAI outbreaks since these countries have a higher GDP level and are able to implement disease surveillance and control plans. In other words, a country with a higher development level may be less affected since they have more capital and advanced technology to combat with disease outbreaks (Burns et al. 2008; Rushton et al. 2006).

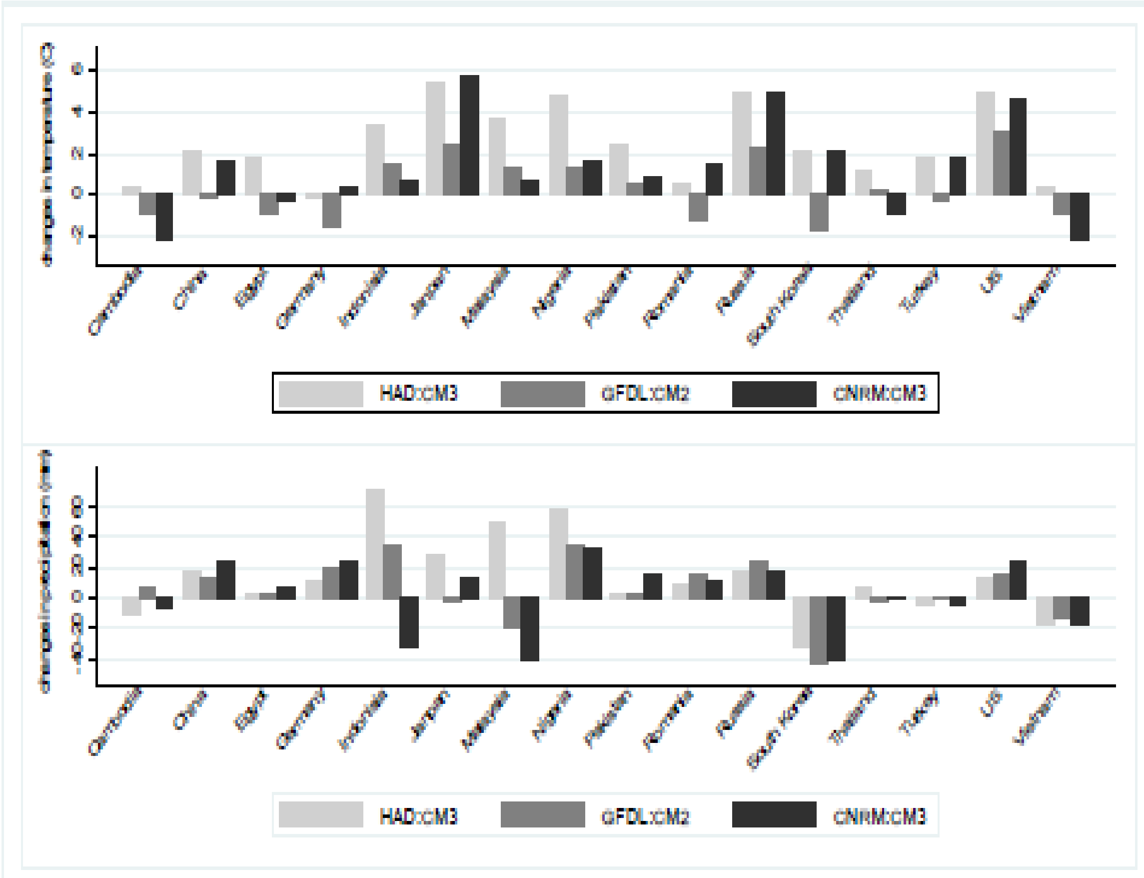


Figure 3-9 Changes in Climate under Three Climate Models[21]

[21] I use the climate in 1961-1990 as the baseline to calculate the difference of temperature and precipitation from climate models by 2011-2030.

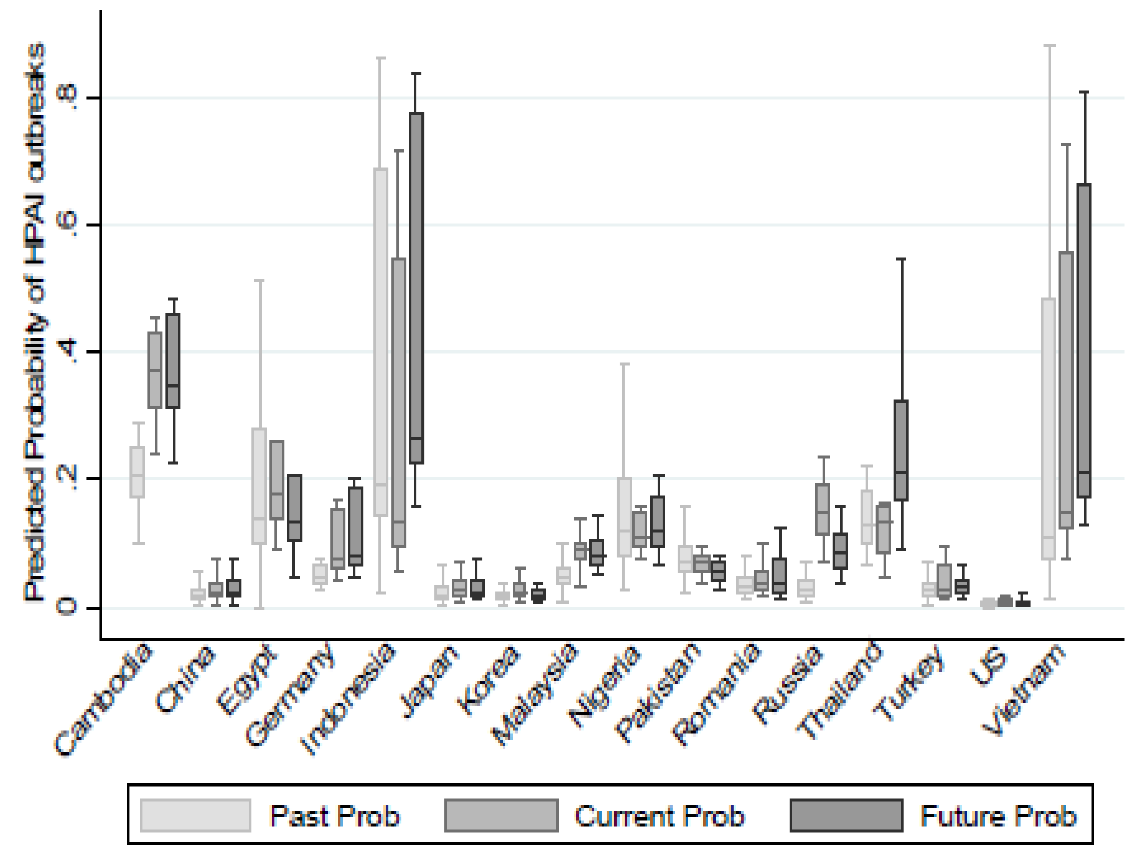


Figure 3-10 Predicted Probability of HPAI Outbreaks under Climate Change

3.6 Economic Loss of HPAI Outbreaks under Climate Change

The next question to answer in this section is what would be the associated economic losses under past and future climate change? Since different countries have different contributions of poultry production to their total GDP, I calculate the additional economic loss by applying the changes of the outbreak probability under climate change to the countries I studied following the estimation procedure used in the World Bank report by Burns et al. (2008)[22]. In addition, considering the underreporting issue, I calibrate the predicted probability of HPAI outbreaks by using the probability of reporting extra zeros. In my calculations I assume,

- When an outbreak occurs that 12% of the domestic birds in each region die from the HPAI disease or are killed to prevent its spread. I use this percentage to calculate the GDP reduction of a further HPAI outbreak due to climate change
- I calculate the averaged percentage of poultry production to the total GDP in each country in 2004-2008 (pp_i) and assume the averaged percentages keep constant in each country over years

For each country i , if assume that the probabilities under past, current and future climate condition is p_{pi} , p_{ci} and p_{fi} (averaged over three climate models), respectively, then $\Delta p_{pi} = p_{ci} - p_{pi}$ and $\Delta p_{fi} = p_{fi} - p_{ci}$ is the difference of HPAI outbreak probability under past and future climate change, respectively. Similarly, for each country i , assume p_{cui} (averaged over three climate models) is the probability of reporting extra zeros under current climate condition, then $1 - p_{cui}$ is the probability of reporting actual HPAI outbreaks. Therefore, I have two equations to calculate the additional economic loss due to past and future climate change, respectively,

[22] According to their study, the reported results are based on a scenario where bird-to bird flu becomes enzootic throughout the world to the degree observed in Vietnam in 2004 (approximately 12 percent of all domestic birds died from the disease or were culled to prevent spread).

(3.24) $Loss_{pi} = \overline{GDP_{pi}} \cdot \Delta p_{pi} \cdot 12\% \cdot pp_i \cdot (1 - p_{cri})$ for $i = 1, \ldots, 16$

(3.25) $Loss_{fi} = \overline{GDP_{fi}} \cdot \Delta p_{fi} \cdot 12\% \cdot pp_i \cdot (1 - p_{cri})$ for $i = 1, \ldots, 16$

where $\overline{GDP_{pi}}$ is the averaged real 2005 GDP between 1971-2000 and $\overline{GDP_{fi}}$ is the averaged projected GDP between 2011 and 2030 in billions of 2005 dollars.

Figures 3-11 and 3-12 show the GDP loss due to HPAI outbreaks under past and future climate, respectively. Additional GDP losses occur across the countries and future climate change generally causes a larger economic loss because of a higher probability of HPAI outbreaks. Comparing two graphs could see that developed countries, such as South Korea and Japan, had insignificant losses relative to their total GDP. However, some developing countries in Asia with relatively small economies and high proportions of poultry production, such as Indonesia, Thailand, and Vietnam, were exposed to a high proportion of losses. Additionally, many countries in our sample have reported more than one HPAI outbreaks since 2003, so the expected economic loss due to past climate change could be larger because of a higher frequency of outbreaks.

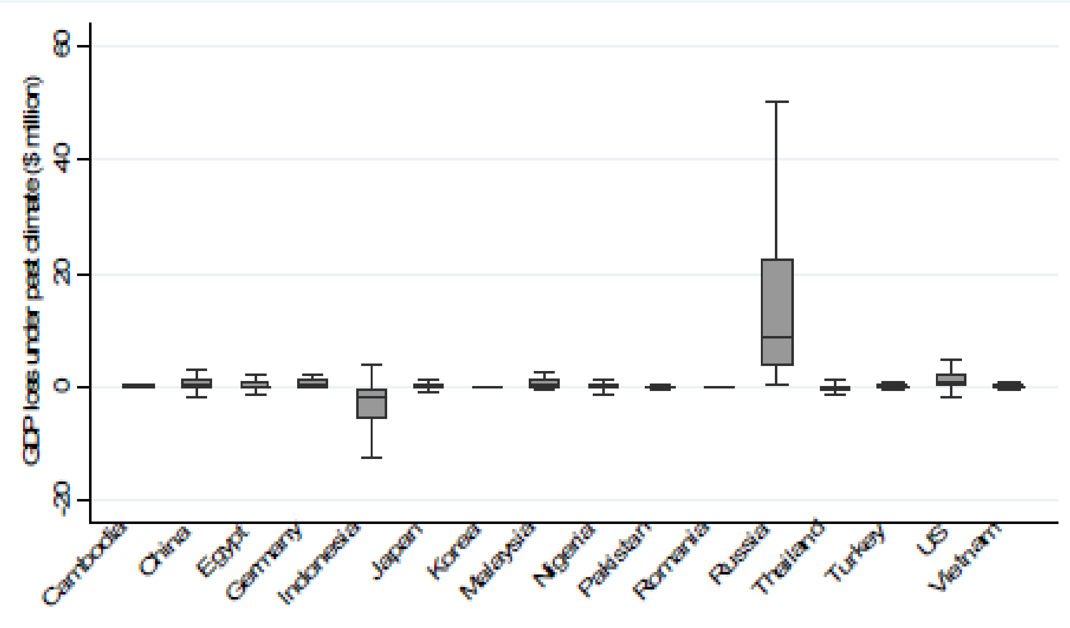


Figure 3-11 GDP Loss Due to HPAI Outbreaks under Past Climate ($ million)

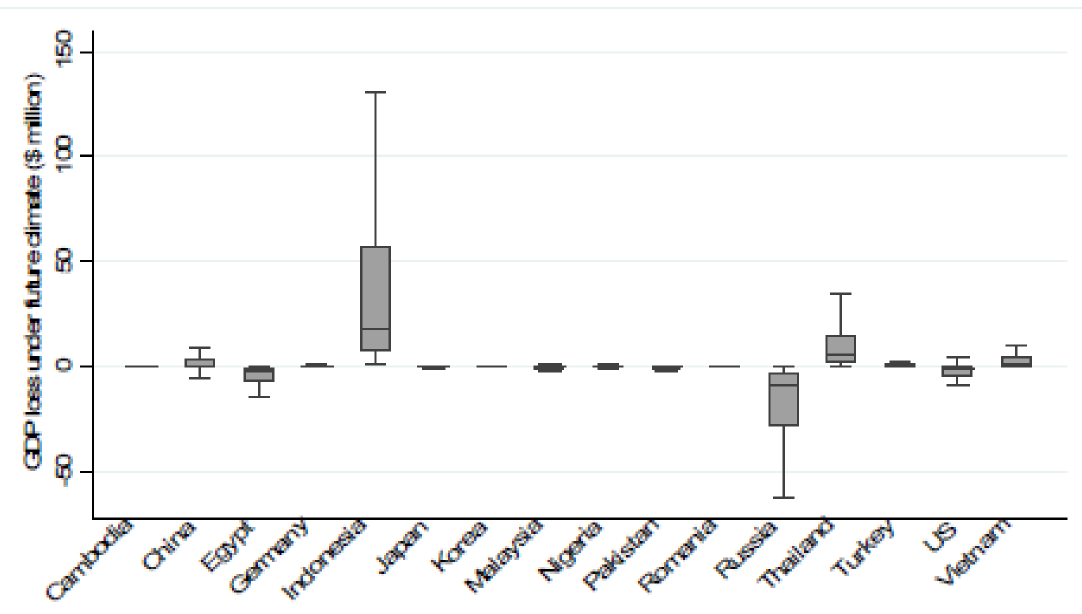


Figure 3-12 GDP Loss Due to HPAI Outbreaks under Future Climate ($ million)

3.7 Concluding Remarks

I examine the relationship between climate conditions and the probability and outcome of HPAI outbreaks. I also evaluate the effects of past and projected climate change on disease outbreak probability and discuss the problem of reporting extra zeros in count outcome. The results show that climate plays an important role in the outbreak probability and expected numbers. In particular, the risk of HPAI outbreaks increases as spring temperature rises or winter precipitation increases. More importantly, countries with lower GDP, larger export of poultry products and more cases of confirmed human death due to HPAI outbreaks will have more incentive to report extra zeros, in other words, they have a high probability to under-report AI outbreaks.

Using data from the past 20 years, out-of-sample prediction shows that past climate change is a contributor to current disease outbreaks with 11% increase in probability. In addition, I also find that increases by 12% in disease outbreak probability under climate change as projected to 2030 across countries. Based on this prediction, countries in lower latitudes with higher temperature in spring and more precipitation in winter would face the largest increase in probability. These areas, in most cases are economically poor regions, so the associated economic loss due to HPAI outbreaks under climate change is significant to these countries. Therefore, it may be desirable to increase surveillance and other control measures in such regions.

4. AI INFORMATION AND MEAT DEMAND IN UNITED STATES

4.1 Introduction

Since the end of 2003, a HPAI--H5N1 virus -- has spread widely reaching almost 60 countries in Asia, Europe and Africa continents, which has caused thousands of poultry depopulated. To date, there are 596 confirmed AI human cases, resulting in 350 human deaths in countries other than the United States[23]. During the same process, United States has several cases of LPAI virus, one H5N2 in poultry, and three Bovine Spongiform Encelopathy (BSE) cases.

These disease outbreaks have received considerable media coverage all over the world, which may affect meat demand in the United States since media coverage of disease outbreaks and spread will hurt consumers' confidence in meat safety. As found in previous studies (Burton and Young 1997; Verbeke and Ward 2001; Piggott and Marsh 2004; Beach and Zhen 2008; Mazzocchi et al. 2006), information regarding food safety/disease incidence could affect consumption patterns, and that negative information can adversely alter the allocation of consumer expenditures on meats.

However, situation may be different if we could trace where and when the animal disease occurred. Since United States is the second largest exporter of poultry meat and poultry product, disease shock on international demand was expected much larger than that on domestic demand. Moreover, changes of meat price based not only on domestic

[23] More information is available via http://www.who.int/influenza/human_animal_interface/H5N1_cumulative_table_archives/en/index.html.

demand shock but also on shift of excess demand. Therefore, taking account of international market effects is very important when analyzing negative impacts of animal disease incidence.

This essay reports on research that examines how information of animal disease incidences (AI and BSE) affects meat demand in the United States using monthly meat consumption data from January 1989 to December 2010. This is done first employing an error corrected demand model to investigate short-run adjustment to the long-run equilibrium and second, using the general error correction model as the benchmark to examine and evaluate out-of-sample forecasting power of two models.

This essay is organized as follows. Section 4.2 summarizes previous literature on demand shocks and food safety issues; Section 4.3 provides data and their statistical descriptions; Section 4.4 introduces models; Section 4.5 presents estimation results and forecasting evaluation and section 4.6 is the concluding remarks.

4.2 Literature Review

A large body of research has considered meat demand shifters including effects of food safety and product recall news (Burton and Young 1996; Mazzochi 2003; 2006; Piggott and Marsh 2004; Beach and Zhen 2008; Verbeke and Ward 2001). In that literature, the studies generally employ the Almost Ideal Demand System (AIDS) model developed by Deaton and Muelbauer (1980), and expand the demand function to use either an information index of the volume of relevant news, or an indicator variable that tells when the event occurred.

Burton and Young (1996) use the index approach in the form of contemporary and cumulative numbers of BSE articles, which allows transitory and permanent quality shocks and find that negative publicity on British beef reduces the beef market share by 4.5% by the end of 1993. Piggott and Marsh (2004) incorporate quarterly media coverage indices of beef, pork, and poultry safety issues separately. They find that heightened public alert over food safety reduces per capita beef, pork, and poultry consumption by 2.21%, 0.99%, and 6.88%, respectively. Piggott et al. (2007) extend Piggott and Marsh (2004)'s study and update the food safety indices until 2005, and their results show that food safety information has a significant impact on consumer demand in the United States.

Beach and Zhen (2008) use media coverage of AI in Italy and find that the short-term AI media index reduces poultry consumption and increases beef demand. They also find that the impacts of newspaper articles on consumers' food choices are determined by the magnitude and duration that the issue was covered. Based on previous studies, Marsh et al. (2004) expand media coverage by adding the total number of recalls in a quarter and find effects of meat recalls on meat demand in the United States are statistically significant but economically small.

Regarding to animal diseases impacts, Ishida et al. (2010) include BSE and AI outbreaks in a study in Japan and find that BSE and AI scares reduce demand for both beef and chicken, while increase demand for substitutes, such as pork and fish products. In stand of using the standard demand model, Mazzocchi (2003) and Mazzocchi et al. (2006) develop a stochastic, time-varying response approach as an alternative to the inclusion of news coverage and apply it to assess the impact of food scare events. He finds that BSE in 1996 is linked with a small negative reduction in beef demand, along with a positive impact on pork and poultry.

However, few studies have paid attention to the time series properties of demand data and not even discussed the possibility that the marginal effects of a single piece of news may not constant over time (Mazzocchi et al. 2006). Most importantly, few studies have evaluated the performance of demand models by testing their forecasting ability.

Therefore, this essay extends previous work addressing shortcomings discussed above. Especially, I test the time series properties of demand data and use directed acyclic graph (DAG) to check causality between price and quantity to determine which type of demand model is appropriate for this study. I then estimate a dynamic demand model to incorporate animal disease index as well as to take account of the time properties of demand data. Finally, I predict out-of-sample forecast to evaluate the performance of the dynamic demand model calculating the root mean squared forecast errors (RMSFE) and the encompassing test.

4.3 Models and Methods

In this section, I first present the static demand model, and then discuss its dynamic form and the general form plus calculations of elasticities.

4.3.1 Form of the Static Demand Model

I use the generalized inverted AIDS demand function following Eales and Unnevehr (1994) by incorporating animal disease information as the shock on the intercept (Duffy 2003), (4.1) $w_i = \alpha_i + \sum_{k=1}^{3} \lambda_{ik} AI_k + \theta_i BSE + \sum_{s=1}^{3} \rho_{is} D_s + \sum_{j=1}^{4} \gamma_{ij} \ln q_j + \beta_i \ln(Q) + u_i$

With

(4.2) $\ln Q = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln q_j + 1/2 \sum_{i=1}^{4} \sum_{j=1}^{4} \gamma_{ij} \ln q_i \ln q_j$

where w_i is the budget share of the i^{th} good; AI_k is the AI information index with $k=1$ indicating a dummy telling when an AI poultry case occurs in United States; $k=2$ giving a count of number of overall AI related newspaper coverage in each month, and $k=3$ giving the cumulative number of AI human cases that occur outside of the United States in each month; BSE is a dummy variable telling when a BSE case occurs in the United States in a month; D_s is a seasonal dummy for the quarters of the year for $s =$ spring, summer or fall; and q_j is the quantity of good j.

In equations (4.1) and (4.2), α, β, γ, ρ, λ, and θ are parameters to be estimated. Restrictions of homogeneity and symmetry are needed but involve only the fixed, unknown coefficients and so may be easily tested or imposed (Eales and Unnevehr 1994). These restrictions are:

(4.3) $\sum_i \alpha_i = 1, \sum_i \beta_i = 0, \sum_i \lambda_{ik} = 0, \sum_i \rho_{is} = 0, \sum_i \theta_i = 0$ adding-up restrictions

(4.4) $\sum_j \gamma_{ij} = 0$, homogeneity restrictions

(4.5) $\gamma_{ji} = \gamma_{ij}$, symmetry restrictions

Specifying the exact form of the demand function involves choice between a nonlinear or linear form. Hahn (1994) suggests estimating AIDS using its nonlinear form because the linear form is an approximate of the nonlinear one. Although estimation results from Eales and Unnevehr (1994) do not reject the linear IAIDS form, they indicate a nonlinear form is preferred. More importantly, elasticities of IAIDS demand function can be calculated directly from its nonlinear form (Green and Alston 1990; 1991). Thus, this essay uses the nonlinear IAIDS[24].

Elasticities from the nonlinear IAIDS demand model are calculated following the same procedure in deriving the elasticities from the nonlinear AIDS (Green and Alston 1990; 1991). For nonlinear IAIDS, Eales and Unnevehr (1994) define the term of flexibilities as the inverse term of elasticities in AIDS, so the interpretation of flexibilities can be made in a manner similar to elasticities. For example, a demand for a commodity is said to be inflexible if a 1% increase in consumption of that commodity leads to a less than 1% decrease in the marginal value of that commodity in consumption (in absolute value). Commodities are termed as gross quantity-substitutes if their cross price flexibility is negative and as gross quantity-complements if it is positive (Eales and Unnevehr 1994).

The interpretation of scale flexibilities can be considered as the case of homothetic preferences. If the scale flexibility of one commodity is less than -1, it means this commodity is a necessity. In other words, the commodity is a luxury good if the scale flexibility is greater than -1.

[24] Set α_0=5 in the Nonlinear Seemly Unrelated Regression (NLSUR) algorithm according to Deaton and Muellbauer (1980).

4.3.2 An Error Corrected Demand Model

Previous studies assume that either price or quantity in the demand system is exogenous (Piggott and Marsh 2004; Verbeke and Ward 2002; Beach and Zhen 2008). However, for aggregated demand data, the presumption of taking price or quantity as given is not appropriate. In addition, consumers' consumption behavior may be changing over time. Thus, an error corrected inverted almost Ideal demand system function, i.e. the ECM-IAIDS, is needed because using a dynamic generating process demand function is able to calculate consumers' consumption preference adjustments (Eakins et al. 2003). The ECM-IAIDS model is based on the static IAIDS demand function identified above (Duffy 2003; 2006)[25].

If assuming quantities and expenditure are weakly exogenous, the ECM-IAIDS model with $m_1 - lag$ is written as below,

$$
\begin{aligned}
\Delta w_t = & \sum_{k=1}^{3} \lambda_k \Delta AI_{kt} + \theta \Delta BSE_t + \sum_{s=1}^{3} \rho_s \Delta D_{st} + \sum_{j=1}^{4} \gamma_j \Delta \ln q_{jt} + \beta(\Delta \ln Q_t) \\
& + \sum_{m_1=1}^{T} \Gamma_{1m_1} \Delta w_{t-m_1+1} + \Pi_1 u_{t-m_1} + \eta_t
\end{aligned} \tag{4.6}
$$

with

$$
\Delta \ln Q_t = \sum_{k=1}^{4} \alpha_k \Delta \ln q_{kt} + 1/2 \sum_{k=1}^{4} \sum_{j=1}^{4} \gamma_{kj} \Delta (\ln q_k \ln q_j)_t \tag{4.7}
$$

[25] DAG results show the causality between price and quantity and finds that quantities are affected by prices, which means an IAIDS model is appropriate.

where Δ represents the first difference operator; Δw_{it-1} captures consumers' habits and $u_{t-m1} = w_{t-m1} - [\alpha + \sum_{k=1}^{3} \lambda_k AI_k + \theta BSE + \sum_{s=1}^{3} \rho_s D_s + \sum_{j=1}^{4} \gamma_j \ln q_j + \beta \ln(Q)]_{t-m1}$ is the estimated residual lag from the static IAIDS model and u_t is assumed to be a white noise stationary series process. Γ_1 is the 3×1 vector and Π_1 is the 3×3 matrix and η_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables. If Π_1 has ranks r_1 and $r_1 < 3$, then w_t is cointegrated with r_1 cointegrating vectors, reflecting a long-run relationship among variables in the system (Wang and Bessler 2003; 2006).

From equations above, the ECM-IAIDS model that incorporates short-run shock is an error correction representation of the static IAIDS model. As stated by Eakins et al. (2003), this dynamic form allows for disequilibrium in the short-run by treating the error term u_i in equation (4.1) as the equilibrium errors and these errors tie the short-run behavior of the dependent variable to its long-run value.

The first-differenced terms on the right hand side capture the short-run disturbances. The error correction term u_{t-m1} captures the long-run equilibrium relationship given by the static IAIDS model and Π_1 measures the speed of adjustment to the long-run equilibrium with $\Pi_1 = 1$ indicating instantaneous adjustment. If Π_1 is large or closer to one in absolute value, then there is a rapid adjustment and a smaller Π_1 indicates a slower speed to go back to the long-run equilibrium.

Flexibilities from the static demand function are treated as the long-run equilibrium and the short-run flexibilities are given by the ECM-IAIDS model. The difference between the long-run and short-run equilibrium is adjusted by Π_1, the coefficient of the error correction term.

4.3.3 A General Error Corrected Model

Since the purpose of this study is to examine the performance of the ECM-IAIDS model giving in a forecasting point of view, it is useful to have a relatively simple base or reference model (Klaiber and Holt 2010). One such possibility is to assume all prices, quantities and expenditures are endogenous, so the general error correction model is chosen, which is presented as below with $m_2 - lag$,

$$(4.8) \quad \Delta y_t = \sum_{m_2=1}^{T} \Gamma_{2m_2} \Delta y_{t-m_2+1} + \Pi_2 y_{t-m_2} + \Phi D_t + \varepsilon_t$$

where Γ_2 is the 9×1 scalar; Π_2 is the 9×9 matrix, Φ is 9×3 matrix; D is the 3×1 vector of seasonal dummies and y_t is 9×1 vector of endogenous variables, including price and quantity of beef, pork, chicken and turkey as well as the total expenditure.

Π_2, Γ_2 and Φ are coefficients to be estimated and ε_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables (Engle and Granger 1987). If Π_2 has a rank r_2 and $r_2 < 9$, then y_t is cointegrated with r_2 cointegrating vectors, reflecting a long-run relationship among variables in the system (Wang and Bessler 2003; 2006)

4.4 Data and Tests

Demand functions for four commodities are estimated including beef, pork, chicken and turkey. Monthly data on retail price and per capita consumption were obtained from the U.S. Department of Agriculture (USDA) and the U.S. Census Bureau sources from January 1989 to December 2010. The beef and pork price data are the averaged retail value, and turkey price is measured by the retail value per pound of whole frozen birds. The chicken price is a composite price averaged across whole bird, chicken breast, and chicken legs weighted by quantity demanded.

The per capita consumption data for chicken and turkey were collected from the USDA Poultry Yearbook. Since the per capita consumption of beef and pork was not available in the USDA Red Meat Yearbook, I divided the total consumption of beef or pork, which is measured by the retail disappearance, by population that was collected from the Population Division of the U.S. Census Bureau, to calculate the per capita consumption of beef or pork.

An AI media index was constructed using the LexisNexis Academic search engine. I searched for news articles related to AI from up to 50 English-language newspapers worldwide. The number of news articles in each month is an AI index in that month. The keywords searched were “avian influenza” or “bird flu” over the period January 1989 to December 2010. Confirmed AI human cases were obtained from the

WHO web site from January 2003[26] to December 2010. Finally, two dummy variables were generated in the model. A BSE-US index indicates whether a BSE case was announced in a month in United States with ones for December 2003, June 2005 and March 2006, and zero for others. An AI-US index indicates whether an AI poultry outbreak was confirmed in each month in United States with ones for November 2003, February 2004 and March 2004, and zero for others. Therefore, I include four animal disease variables,

- A dummy variable indicating whether the AI poultry case occurred in the United States as a shock on domestic meat demand (AI-US)
- A counted number of articles covering AI outbreaks information as a shifter for both domestic and international demand (AI-media coverage)
- A variable identifying the cumulative number of confirmed AI human deaths reported by WHO as a shock on the international demand (AI-human deaths)
- A dummy of whether a BSE event occurred in the United States (BSE-US)

Figure 4-1 shows the expenditure share of beef, pork and chicken during January 1989 and December 2010. The vertical dash line indicates the first BSE case in the United States on December 2003 and the vertical solid line indicates the most dangerous H5N2 AI case in Texas on February 2004. With the first BSE announcement, beef expenditure dropped and chicken expenditure went up slightly. However, with the H5N2 AI case, there was no significant shift of meat expenditure. It is possible because of

[26] The WHO only provides confirmed AI human cases since January 2003, so I assume that there was no confirmed AI human case before that. I also checked webpage information, and it seems that no confirmed AI human case was reported before 2003.

interaction effects spill over beef and chicken demand, which probably offset positive and negative effects among demand of meat.

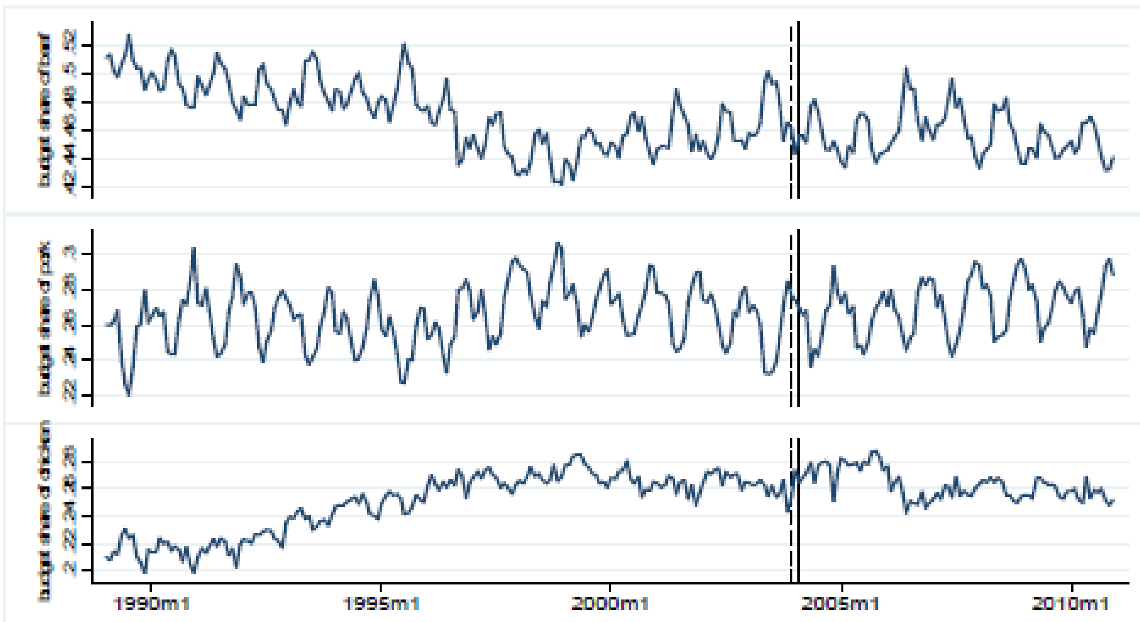
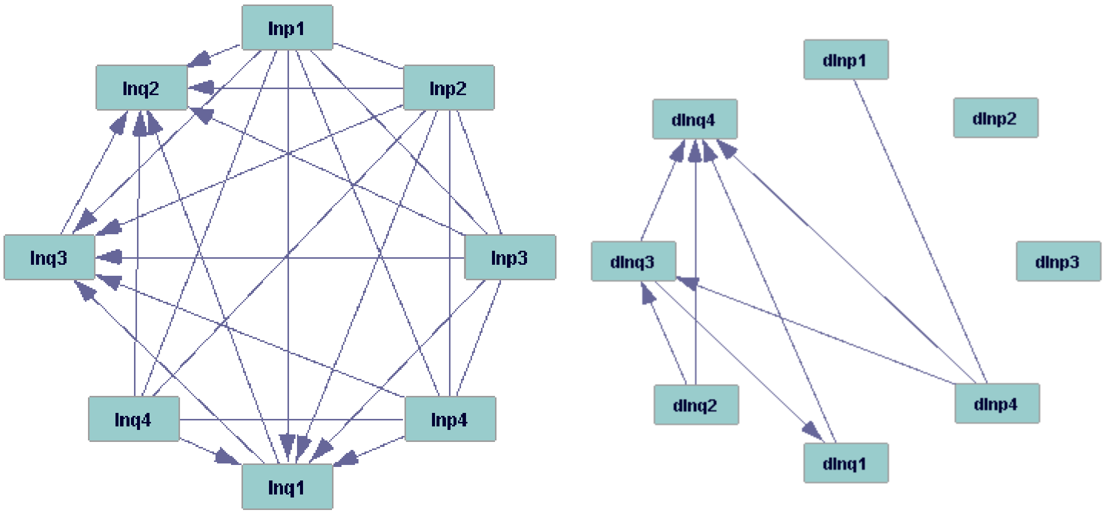


Figure 4-1 Meat Expenditure Patterns for Beef, Pork and Chicken

Based on the assumption that price is predetermined (Deaton and Muellbauer 1980) or the quantity consumed is predetermined (Eales and Unnevehr 1994; Klaiber and Holt 2010), two types of demand models are applied in demand estimation. This is a quantity-dependent demand function (e.g. AIDS) or a price-dependent demand function (e.g. IAIDS). As shown in Wang and Bessler (2006), this empirical modeling strategy has a problem because the choice between price-dependent and quantity-dependent functions remains arbitrary and is not trivial. To avoid possible problems associated with the choice of functional forms, I test for causal relationship between price and quantity at level and at the first difference as well.

According to Wang and Bessler (2006), the causality between price and quantity could be examined by using the Directed Acyclic Graph (DAG). I employ TETRADIV with the GES algorithm to identify the contemporaneous causal flows between prices and quantities. Figure 4-2 shows the causal relationships among prices and quantities, all are in logged term. Arrows indicate that beef (lnq1), pork (lnq2) and chicken (lnq3) quantities are affected by their own prices, while the causality between turkey price (lnp4) and its quantity is unidentified. In fact, turkey takes a small proportion of total meat consumption and the commodity with the smallest consumption is usually the equation dropped in demand system estimation, so the relationship between turkey price and quantity becomes negligible[27]. When looking at the first difference level, chicken and turkey quantities are both affected by turkey price and there is no direct causality between price and quantities of beef and pork, respectively.

[27] Actually, DAG in pattern shows that turkey quantity is affected by its own price.



$\lambda^2 = 1.72$, $\text{P}-value = 0.632$, $\text{BIC} = -15.01$ $\lambda^2 = 33.96$, $\text{P-value} = 0.026$, $\text{BIC} = -77.49$

Figure 4-2 Causalities among Prices and Quantities

Figure 4-2 suggests that a price-determined demand function is not appropriate (e.g. AIDS model), so a quantity-predetermined demand function should be used under the assumption that quantities and expenditures are weakly exogenous. Otherwise, a general error correction model should be used with the assumption that quantities and expenditures are endogenous (Wang and Bessler 2006). Considering time series properties of demand data, I first apply the two-step demand model proposed by Morana (2000) and Mazzocchi et al. (2006), and then use the general error correction model to release the assumption of weakly exogenous[28].

4.5 Results

In this section, I first test time series properties of demand data, then interpret results from the static IAIDS model along with the long-run flexibilities, and results from the dynamic ECM-IAIDS model along with the short-run flexibilities. Finally, I evaluate forecasting performance between the ECM-IAIDS and the general ECM model.

4.5.1 Testing Time Series Properties of Demand Data

Before interpreting estimation results, variables are tested to check whether they have unit root by using the Augmented Dickey-Fuller (ADF) t test. Table 4-1 presents ADF test results showing that turkey budget share, price of beef, pork, chicken and turkey have unit roots and other variables are stationary at the 5% confidence level. All variables are stationary at the 1% confidence level at their first-difference.

It is known that one weakness of the ADF test is its potential confusion of structural breaks in the series as evidence of nonstationarity. Therefore, test proposed by Clemente et al. (1998) is used since it allows for structure breaks. Table 4-1 also reports results of unit root test with one structure break.

[28] Due to the assumption of weakly exogenous in the demand model, the purpose of using the general error correction model (ECM) is to test the robustness of the two-step demand estimation. Initially, the ECM model has no economic meaning for estimated parameters, but it could be helpful to release the exogenous assumption and determine the forecasting ability when doing the evaluation of the two-step demand model.

Consistently, most variables at level cannot reject the null hypothesis of unit root with one structure break, and all variables at the first difference reject the null hypothesis of unit root, which means that demand data at level have unit roots and thus in the absence of cointegration. In other words, parameters and elasticities estimates from demand models at level are spurious (Eakins et al. 2003; Mazzocchi et al. 2006).

There are two popular ways to determine the rank and lag in the ECM-IAIDS and the ECM model. The conventional approach is a two-step procedure involving system-based LR tests to determine r and k sequentially (Park et al. 2008). This procedure is first to determine the lag length using information matrices, and then to determine the rank of cointergration vectors based on a trace test (Johansen1988). The second approach is the model selection method based on information criteria (Aznar and Salvador 2002; Baltagi and Wang 2007; Phillips and McFarland 1997; Park et al. 2008).

Table 4-1 Unit Root Tests with and without Structural Break

Variable	Description	ADF Test		Clemente, Montanes and Reyes (1998) Test			
		For zero structure break		For one structure break (IO model)		For one structure break (AO model)	
		Level	Difference	Level	Difference	Level	Difference
w1	Budget share of beef	-4.250**	-14.965**	-3.947	-5.456**	-2.811	-4.421**
w2	Budget share of pork	-5.730**	-13.221**	-2.918	-5.401**	-2.362	-4.764**
w3	Budget share of chicken	-3.386**	-21.855**	-3.573	-5.232**	-2.928	-5.489**
w4	Budget share of turkey	-2.568	-13.764**	-4.372**	-4.4**	-0.945	-5.976**
lnp1	Retail price of beef (cents/lb)	-0.358	-13.013**	-3.151	-5.761**	-2.714	-3.85**
lnp2	Retail price of pork(cents/lb)	-0.921	-12.911**	-2.93	-4.396**	-3.054	-3.295
lnp3	Retail price of chicken(cents/lb)	-2.000	-19.756**	-2.391	-9.436**	-3.664**	-9.98**
lnp4	Retail price of turkey(cents/lb)	-3.954**	-15.416**	-2.043	-5.427**	-0.649	-5.002**
lnq1	Consumption of beef (lb/capita)	-10.275**	-30.243**	-3.499	-7.569**	-1.982	-7.639**
lnq2	Consumption of pork(lb/capita)	-8.259**	-25.916 **	-2.082	-5.749**	-2.006	-5.629**
lnq3	Consumption of chicken(lb/capita)	-4.449**	-34.857**	-2.365	-8.632**	-1.912	-12.53**
lnq4	Consumption of turkey(lb/capita)	-10.461**	-25.291**	-2.371	-6.958**	-1.868	-4.744**
lnexp	Expenditure on meat (cents/capita)	-3.527**	-34.655**	-1.195	-6.891**	-1.15	-7.096**
5% critical value		-2.879	-2.880	-4.27	-4.27	-3.56	-3.56

Note: the null hypothesis of Augmented Dickey-Fuller test is that there is a unit root at some level of confidence; ** indicates we cannot accept the null hypothesis of a unit root at the 5% critical value. The AO model captures a sudden change in a series and the IO model allows for a gradual shift in the mean of the series.

Table 4-2 reports selection-order criteria for lag m_1 and Johansen tests for cointegration r_1. It can be seen that different information criteria give different length of lags, which could affect rank for cointegration. If choosing $m_1 = 2$ or $m_1 = 3$, there are $r_1 = 2$ for sample before disease outbreaks in United States and $r_1 = 0$ for the whole sample. However, it is difficult to determine the rank for the sample after disease outbreaks in the United States since there is zero rank if $m_1 = 2$, and two ranks if $m_1 = 3$.

Therefore, a more advanced model selection procedure is used to determine the lag and rank simultaneously. Table 4-3 provides information criteria from model selection approach and finds that $m_1 = 2$ and $r_1 = 2$ has the minimum Hannan and Quinn loss (HQIC) as well as the minimum Schwarz-loss criterion (BIC) loss for both subsamples for the ECM-IAIDS model.

Table 4-2 Selection of m_1 and Johansen Tests for r_1

	Selection-order Criteria for Lag			Johansen Tests for Cointegration	
Rank	AIC	HQIC	BIC	Lag=2	Lag=3
	1989m1-2003m10 (before animal disease outbreaks in United States)				
0	-18.1863	-18.1642	-18.1318	81.4043	77.9229
1	-22.8225	-22.7341	-22.6046	26.8317	19.1338
2	-23.0637	-22.9091*	-22.6825*	2.9682*	2.6257*
3	-23.064*	-22.8431	-22.5194		
4	-23.0581	-22.7708	-22.35		

Table 4-2 Continued

	Selection-order Criteria for Lag			Johansen Tests for Cointegration	
Rank	AIC	HQIC	BIC	Lag=2	Lag=3
	1989m1-2006m7(after animal disease outbreaks in United States)				
0	-18.2971	-18.2776	-18.2488	93.0585	91.6218
1	-22.7335	-22.6554	-22.5403	34.3344	23.573
2	-22.9378	-22.801*	-22.5997*	4.0414	3.3972*
3	-22.9842*	-22.7889	-22.5012		
4	-22.9635	-22.7096	-22.3356		
	1989m1-2010m12 (whole sample)				
0	-18.1603	-18.1438	-18.1192	101.2958	103.9294
1	-22.8086	-22.7426	-22.6443	33.5604	21.8731
2	-23.0387	-22.923	-22.7511*	5.2282	4.1758
3	-23.1165*	-22.9513*	-22.7056		
4	-23.1097	-22.8949	-22.5756		

Note: in this table, $AIC = 2k - 2\ln(L)$ where k is the number of parameters in the statistic model and L is the maximized value of the likelihood function for the estimated model; $BIC = n\ln(\hat{\sigma}_e^2) + k\ln(n)$, where $\hat{\sigma}_e^2$ is the error variance for the estimated model; $HQIC = n\log(\frac{RSS}{n}) + 2k\log\log(n)$, where n is the number of observation and RSS is the residual sum of squares that results from the statistical model.

Table 4-3 Model Selection Procedure for Rank (r_1) and Lag (m_1)

Lag	Rank	1989m1-2003m10		1989m1-2006m7	
		HQIC	BIC	HQIC	BIC
1	1	-22.706	-22.6207	-22.6124	-22.5365
1	2	-22.7689	-22.6516	-22.6808	-22.5764
2	1	-22.8627	-22.6807	-22.7269	-22.5649
2	2	**-22.9423**	**-22.7282**	**-22.8237**	**-22.6332**
3	1	-22.8249	-22.5454	-22.7532	-22.5047
3	2	-22.8629	-22.5512	-22.8019	-22.5248
4	1	-22.7551	-22.3774	-22.6804	-22.3448
4	2	-22.7761	-22.366	-22.7102	-22.3458
5	1	-22.8341	-22.3575	-22.715	-22.2917
5	2	-22.829	-22.3199	-22.7152	-22.263

Based on the rank and lag selection results, I estimate the ECM-IAIDS model with $r_1 = 2$ and $m_1 = 2$ using a one-step, simultaneous, non-linear seemingly unrelated regression (NLSUR) approach (McElroy et al. 1988). This method also allows for correlations in the residual variance-covariance matrix and will lead to more efficient estimation for small samples. In addition, Elder (1997) finds that this NLSUR algorithm is more stable and robust with respect to poor initial values.

For the general ECM model, I use the model selection approach to determine m_2 and r_2. Figure 4-3 shows the minimum point from BIC is at $r_2 = 4$ and $m_2 = 1$. Therefore, I estimate the general ECM model with $r_2 = 4$ and $m_2 = 1$.

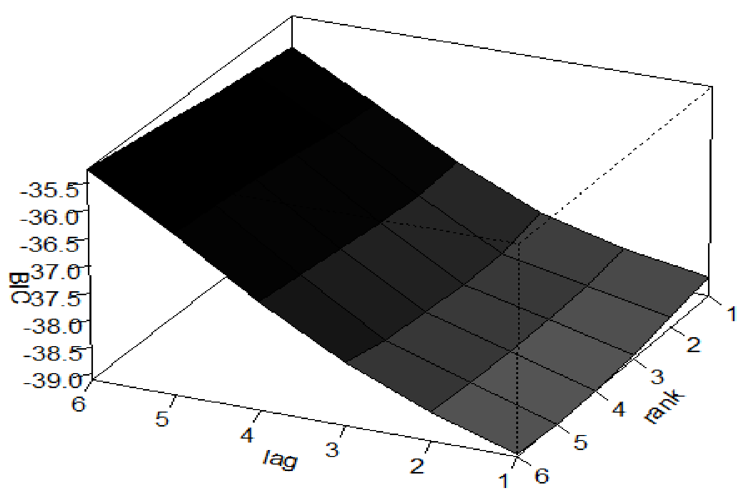


Figure 4-3 Rank (r_2) and Lag(m_2) Selection for the ECM Model

4.5.2 Estimation Results

For the static IAIDS model, estimated parameters for the budget share equations are presented in Table 4-4 with model diagnostics. The results presented here are from a regression over three samples including January 1989 to October 2003, January 1989 to July 2006 and the whole sample. Since all variables entering the static regression are stationary in first-difference, interpreting the results from this regression relies on the stationary of residuals. ADF t test is used to test whether residuals from the static IAIDS equations are stationary and results in Table 4-4 reject the null hypothesis of unit roots at the 1% confidence level. Thus, the following results can be stated.

If only consider impacts of AI media coverage, results from sample from January 1989 to October 2003 show that it only increases pork budget share and has insignificant impacts on other meat. Under a static situation, the confirmed AI human deaths in other countries affect beef expenditure positively and chicken expenditure negatively over two subsamples. In particular, impacts of overseas AI human deaths on U.S. demand are statistically significant though economically small, equaling 0.02% for beef, -0.005% for pork, and -0.01% for chicken for subsample from January 1989 to July 2006. Moreover, it has smaller impacts on meat expenditure when using the whole sample.

Since AI human cases have not occurred in the United States and there were only several poultry cases in history, it seems that nearby outbreaks and deaths would have larger effects than overseas' disease outbreak information. This is also suggested by results from the general AI media coverage all over the world because it has positive and significant impact on chicken expenditure for the sample from January 1989 to July

2006 and increases beef expenditure and reduces pork expenditure in the whole sample. Therefore, distinguishing where the information comes from is necessary when defining situations like animal disease.

For BSE events, they increase pork expenditure and decrease chicken expenditure in the whole sample, and have insignificant effects on beef. It is suspected that AI effects, which come from strongly and intensively media reports of AI disease spread and human deaths, will offset impacts of BSE events. Nevertheless, results show that adverse information from the nearby disease outbreaks has negative impacts on meat demand and this is consistent to previous study by Piggott and Marsh (2004) and Beach and Zhen (2008). The later also argue that similar but smaller impacts on chicken consumption in the United States would be expected.

Table 4-5 reports the uncompensated own and cross flexibilities as well as the scale (expenditure) flexibilities along with the appropriate standard errors from the static IAIDS model. All the flexibilities were calculated at the sample means. Note that all own-quantity flexibilities are negative as theoretically expected, and all own-quantity flexibilities estimates were less than one in absolute value, indicating beef, pork and chicken demands in the United States are quantity inflexible. In addition, beef, pork and chicken are substitutes with all signs negative, which is consistent with results in Eales and Unnevehr (1994).

When looking at the AI media coverage flexibility, it is interesting to see that in a long run, it increases pork consumption if only considering overseas disease outbreaks. However, it increases chicken consumption and reduces pork consumption if taking account of domestic animal disease outbreaks. It is possible due to shocks on international market, consumers benefit from a lower price of chicken. Alternative reason is people may switch to chicken when BSE disease is announced. Since AI and BSE disease occurred across each other, both possibilities exist in a long-run equilibrium, while a short-run analysis could tell which reason is more important.

As expected, information related to human deaths causes more attention from people and they become more cautious when purchasing meat. In the long run, beef consumption increases as the number of confirmed AI human deaths increases, while pork and chicken consumption decreases.

Table 4-4 Estimation Results from the Static IAIDS with Model Diagnostics

		Model Estimation				Model Diagnostics			
		AI-US	AI-media coverage	AI-human death	BSE-US	DW test on residual	Unit root test on residual	RMSE	R^2
1989m1	Beef		-0.0036			2.2164	-8.340***	0.0080	0.9997
-			(0.0023)						
2003m10	Pork		0.0032*			2.5930	-8.629***	0.0060	0.9995
			(0.0017)						
	Chicken		0.0001			1.8368	-8.180***	0.0069	0.9992
			(0.0019)						
1989m1	Beef	1.0231*	-0.0006	0.0168***	-0.3473	1.9522	-5.051***	0.0092	0.9996
-		(0.5730)	(0.0004)	(0.0023)	(0.4321)				
2006m7	Pork	-0.4283	-0.0002	-0.0051***	0.9061	2.2027	-8.103***	0.0071	0.9993
		(0.4352)	(0.0003)	(0.0018)	(0.5625)				
	Chicken	-0.5372	0.0007**	-0.0136***	-0.6775	1.5601	-5.292***	0.0068	0.9993
		(0.4232)	(0.0003)	(0.0017)	(0.4140)				
1989m1	Beef	0.8375	0.0005*	0.0052***	-0.3704	2.5680	-9.995***	0.0085	0.9997
-		(0.5184)	(0.0003)	(0.0005)	(0.3862)				
2010m12	Pork	-0.4167	-0.0005**	-0.0022***	1.1046**	2.4600	-10.460***	0.0064	0.9994
		(0.3916)	(0.0002)	(0.0004)	(0.5075)				
	Chicken	-0.3822	-0.0001	-0.0055***	-0.6996**	2.4733	-11.409***	0.0058	0.9995
		(0.3541)	(0.0002)	(0.0003)	(0.3475)				

Note: Coefficients and standard errors in this table are multiplied by 100 to make them more comparable; * $p<0.1$, ** $p<0.05$, and *** $p<0.01$; Standard errors are in parenthesis.

Table 4-5 Long-run Own- and Cross-Price and Expenditure Flexibilities

	1989m1-2003m10			1989m1-2006m7			1989m1-2010m12		
	Beef	Pork	Chicken	Beef	Pork	Chicken	Beef	Pork	Chicken
Beef	-0.8713***	-0.1457***	-0.0885***	-0.9248***	-0.1156***	-0.0774***	-0.8914***	-0.1266***	-0.0700***
	(0.0248)	(0.0093)	(0.0057)	(0.0251)	(0.0083)	(0.0055)	(0.0193)	(0.0067)	(0.0040)
Pork	-0.1119***	-0.8316***	-0.0142***	-0.0405	-0.8412***	-0.0283***	-0.0677***	-0.8347***	-0.0251***
	(0.0254)	(0.0112)	(0.0037)	(0.0301)	(0.0086)	(0.0051)	(0.0223)	(0.0074)	(0.0048)
Chicken	0.0036	0.0139	-0.8590***	0.0346	-0.0117	-0.8600***	-0.0103	-0.0242***	-0.8568***
	(0.0363)	(0.0145)	(0.0083)	(0.0340)	(0.0125)	(0.0082)	(0.0230)	(0.0079)	(0.0030)
Expenditure	-1.0771***	-0.9773***	-0.8737***	-1.0998***	-0.9192***	-0.8573***	-1.0681***	-0.9269***	-0.9248***
	(0.0261)	(0.0343)	(0.0443)	(0.0261)	(0.0356)	(0.0386)	(0.0216)	(0.0288)	(0.0290)
AI media	-0.0072	0.0112**	0.0005	-0.0012	-0.0008	0.0025**	0.0010	-0.0018**	-0.0005
coverage	(0.0046)	(0.0060)	(0.0071)	(0.0008)	(0.0010)	(0.0010)	(0.0005)	(0.0007)	(0.0007)
AI human				0.0324***	-0.0171***	-0.0482***	0.0100***	-0.0076***	-0.0196***
deaths				(0.0044)	(0.0059)	(0.0061)	(0.0009)	(0.0013)	(0.0011)

Note: I calculated the Marshallian own- and cross price flexibilities using equation $\varepsilon_{ij} = -\delta_{ij} + \frac{\gamma_{ij} + \beta_i(\alpha_j + \sum_{i=1} \gamma_{ij} \ln q_k)}{w_i}$ and the expenditure flexibilities using equation $f_i = -1 + \frac{\beta_i}{w_i}$, where δ_{ij} is the Kronecker delta with $\delta_{ij} = 1$ if $i = j$ and $\delta_{ij} = 0$ if $i \neq j$. * p<0.1, ** p<0.05, and *** p<0.01; Standard errors are in parenthesis.

There are three criteria to determine a preferred long-run equilibrium model (Eakins et al. 2003), which could be used for estimating the dynamic one.

- Whether the estimated flexibilities imply a downward sloping demand curve
- Whether the regression model passes various diagnostic tests including goodness-of-fit, serial correlation, etc.
- Whether the model indicates a stationary pattern of residuals

As shown in Tables 4-4 and 4-5, model diagnostics and estimated flexibilities suggest that the static IAIDS model meets all three criteria. Table 4-6 reports regression results from the ECM-IAIDS model based on equation (4.6) and (4.7).

The error correction term Π_1 for beef is -12% when there was no AI and BSE outbreak in the United States, which implies that 12% of the disturbance to the long-run equilibrium in the previous period is corrected or adjusted back to long-run equilibrium in this period. However, with the animal disease outbreaks, the adjustment rate is 30%, indicating there is quick adjustment after disease outbreaks. For chicken expenditure, 11% of the disturbance to the long-run equilibrium is adjusted when there were AI outbreaks overseas, and the adjustment rate decreases to 0.3% and 4% if there are AI and BSE outbreaks occurred in the United States, suggesting there is a slower adjustment speed for chicken demand.

In the short run, information on overseas' disease outbreaks is insignificant on meat expenditure. However, information on domestic disease outbreaks has statistically significant impacts. Beef expenditure increases as AI outbreaks and decreases as BSE outbreaks. Moreover, pork expenditure goes up as BSE outbreaks. Results also show shifts in consumers' meat demand habits are significant at the 1% confidence level for all three samples, which indicates consumers are persistent to their consumption behaviors over time.

Table 4-7 gives estimates of short-run own- and cross-price and expenditure flexibilities. The short-run own-price flexibilities of beef, pork and chicken are close to their long-run flexibilities. Combined with the error correction coefficients in Table 4-6, the quantity frequencies of demand for beef, pork and chicken do not move far from their long-run frequencies.

Table 4-6 Estimation Results from the ECM-IAIDS Model

		AI-US	AI-media coverage	AI-human death	BSE-US	Δw_{t-1}	$u_{beef,t-2}$	$u_{pork,t-2}$	$u_{chicken,t-2}$	RMSE	R^2
1989m1-2003m10	Beef		0.0336			-11.1821***	-11.9550*	-12.3468	-3.5983	0.0040	0.8725
			(0.0334)			(2.5491)	(6.5747)	(8.2662)	(6.3261)		
	Pork		0.0179			-7.9512***	4.0262	3.3013	4.3918	0.0031	0.9290
			(0.0255)			(2.3362)	(5.0379)	(6.3276)	(4.8332)		
	Chicken		-0.0261			-6.1812**	-3.7455	-6.6925	-10.5372**	0.0034	0.7391
			(0.0283)			(3.1049)	(5.5451)	(7.0431)	(5.3526)		
1989m1-2006m7	Beef	0.5226**	0.0084	0.0041	-0.3989***	-12.7952***	-29.9868***	-24.9069***	-19.7354**	0.0043	0.8533
		(0.2356)	(0.0339)	(0.0084)	(0.1288)	(2.3516)	(7.6247)	(8.7519)	(8.5523)		
	Pork	-0.2292	0.0105	0.0052	0.3710**	-9.3800***	5.6888	0.7484	-3.0699	0.0030	0.9323
		(0.1613)	(0.0232)	(0.0058)	(0.1873)	(2.1080)	(5.2317)	(6.1330)	(6.1115)		
	Chicken	-0.2843	-0.0060	-0.0113	0.0025	-7.6040***	4.4136	1.5689	-0.3776	0.0039	0.7188
		(0.2144)	(0.0308)	(0.0076)	(0.1722)	(2.7641)	(6.9959)	(8.1480)	(7.7560)		
1989m1-2010m12	Beef	0.5211**	0.0124	0.0020	-0.4188***	-10.9211***	-30.1533***	-13.2837**	-20.8174**	0.0045	0.8413
		(0.2374)	(0.0336)	(0.0067)	(0.1346)	(2.1534)	(8.5169)	(6.5043)	(9.4714)		
	Pork	-0.1971	0.0015	0.0016	0.3961**	-9.2270***	1.7190	4.4262	0.3583	0.0032	0.9233
		(0.1673)	(0.0237)	(0.0047)	(0.1909)	(1.9230)	(5.9993)	(4.4580)	(6.6950)		
	Chicken	-0.3040	-0.0017	-0.0058	-0.0126	-7.9034***	4.6507	-4.7119	-4.1110	0.0040	0.6983
		(0.2126)	(0.0300)	(0.0059)	(0.1726)	(2.4709)	(7.6468)	(5.8834)	(8.4790)		

Note: coefficients and standard errors in this table are all multiplied by 100 to make them more comparable; * $p<0.1$, ** $p<0.05$, and *** $p<0.01$; Standard errors are in parenthesis.

Table 4-7 Short-run Own- and Cross-Price and Expenditure Flexibilities

	1989m1-2003m10			1989m1-2006m7			1989m1-2010m12		
	Beef	Pork	Chicken	Beef	Pork	Chicken	Beef	Pork	Chicken
Beef	-0.7936***	-0.1183***	-0.0935***	-0.7978***	-0.1111***	-0.0958***	-0.7951***	-0.1109***	-0.0969***
	(0.0092)	(0.0049)	(0.0082)	(0.0093)	(0.0047)	(0.0084)	(0.0086)	(0.0043)	(0.0076)
Pork	-0.1193***	-0.8084***	-0.0622***	-0.1120***	-0.8117***	-0.0684***	-0.1115***	-0.8100***	-0.0692***
	(0.0052)	(0.0049)	(0.0052)	(0.0048)	(0.0043)	(0.0051)	(0.0045)	(0.0040)	(0.0045)
Chicken	-0.0914***	-0.0635***	-0.8412***	-0.0939***	-0.0696***	-0.8317***	-0.0950***	-0.0706***	-0.8319***
	(0.0088)	(0.0052)	(0.0107)	(0.0089)	(0.0050)	(0.0107)	(0.0080)	(0.0045)	(0.0094)
Expenditure	-1.0254***	-0.9967***	-0.9756***	-1.0245***	-0.9932***	-0.9819***	-1.0277***	-0.9842***	-0.9858***
	(0.0088)	(0.0118)	(0.0145)	(0.0088)	(0.0108)	(0.0153)	(0.0079)	(0.0098)	(0.0134)
AI media coverage	0.0676	0.0633	-0.0969	0.0170	0.0372	-0.0224	0.0250	0.0052	-0.0064
	(0.0673)	(0.0901)	(0.1050)	(0.0682)	(0.0820)	(0.1143)	(0.0677)	(0.0837)	(0.1115)
AI human deaths				0.0079	0.0177	-0.0401	0.0038	0.0055	-0.0205
				(0.0162)	(0.0195)	(0.0270)	(0.0128)	(0.0159)	(0.0211)

Note: * p<0.1, ** p<0.05, and *** p<0.01; Standard errors are in parenthesis.

Following Deaton and Muellbauer (1980), symmetry and homogeneity constraints are tested using the LR test, which is written as,

(4.9) $T_1 = -2(\log L^R - \log L^*)$

where L^R is the likelihood from the restricted estimation and L^* is from the unrestricted estimation. Since the standard LR test approach provides biased results toward rejection of the null hypothesis (Meisner 1979), three alternative test statistics as proposed by Deaton(1972;1974) and Baldwin et al. (1983) are also used, which are presented below,

(4.10) $T_2 = T \times tr[(\tilde{\Omega}^R)^{-1}(\tilde{\Omega}^R - \tilde{\Omega}^*)]$

(4.11) $T_3 = \dfrac{tr[(\tilde{\Omega}^R)^{-1}(\tilde{\Omega}^R - \tilde{\Omega}^*)]/[(n/2)(n-1)]}{tr[(\tilde{\Omega}^R)^{-1} \times \tilde{\Omega}^*]/(n-1)[T-k]}$

(4.12) $T_4 = \dfrac{tr[(\tilde{\Omega}^R)^{-1}(\tilde{\Omega}^R - \tilde{\Omega}^*)]}{tr[(\tilde{\Omega}^R)^{-1} \times \tilde{\Omega}^*]/(n-1)[T-k]}$

In all three equations, $\tilde{\Omega}^R$ is the estimated variance-covariance matrix of the error terms from the restricted model and $\tilde{\Omega}^*$ is from the unrestricted model; n is the number of equations, k is the number of explanatory variables and T is the total observations for estimation. T_1, T_2 and T_4 are all asymptotically distributed as $\lambda^2[n(n-1)/2]$ under the null hypothesis and T_3 is asymptotically distributed as $F(n(n-2)/2,(n-1)[T-(n+2)])$ under the null hypothesis.

Table 4-8 reports test results from T_1 to T_4 with significant level. It can be seen that the null hypothesis that homogeneity, or symmetry, or both restrictions hold is rejected at the 1% confidence level in the static IAIDS model. However, for all test statistics, results cannot reject the null hypotheses that economic restriction holds at the 1% confidence level in the ECM-IAIDS model for two subsamples, which suggests that imposing the dynamic term of consumption habits and the adjustments of short-run disturbance from the long-run equilibrium is helpful to explain U.S. meat demand patterns.

Table 4-8 Tests of Homogeneity and Symmetry in Demand Models

Model		Unrestricted V.S. Homogeneity (3)	Unrestricted V.S. Symmetry (3)	Homogeneity V.S. Restricted (3)	Symmetry V.S. Restricted (3)	Unrestricted V.S. Restricted (6)
	1989m1-2003m10					
IAIDS	T1	26.26 ***	34.74 ***	27.77***	19.29***	54.03***
	T2	21.93***	31.61***	26.61***	18.24***	47.80***
	T3	4.12***	6.06***	5.05***	3.40**	9.48***
	T4	12.37***	18.17***	15.15***	10.21**	28.43***
ECM-IAIDS	T1	9.64**	0.68	0.9	9.86**	10.54
	T2	9.34**	0.68	0.90	9.56**	10.22
	T3	1.47	0.11	0.14	1.51	1.61
	T4	4.41	0.32	0.42	4.52	4.84
	1989m1-2006m7					
IAIDS	T1	28.29***	26.33***	17.14***	19.10***	45.43***
	T2	17.55***	21.17***	16.71***	17.51***	33.95***
	T3	4.99***	7.23***	4.14***	4.15***	4.26***
	T4	14.96***	21.69***	12.43***	12.44***	12.79**
ECM-IAIDS	T1	7.87**	8.40**	3.48	2.95	11.35*
	T2	7.67	8.07	3.47	2.88	11.06*
	T3	1.87	0.14	1.90	1.90	1.92*
	T4	5.60	0.41	5.70	5.69	5.77

Table 4-8 Continued

Model		Unrestricted V.S. Homogeneity (3)	Unrestricted V.S. Symmetry (3)	Homogeneity V.S. Restricted (3)	Symmetry V.S. Restricted (3)	Unrestricted V.S. Restricted (6)
	1989m1-2010m12					
IAIDS	T1	43.93***	22.51***	12.99***	34.41***	56.92***
	T2	38.91***	21.01***	12.74***	32.56***	50.98***
	T3	7.78***	9.50***	5.42***	5.57***	5.70***
	T4	19.80***	28.49***	16.27***	16.70***	17.11***
ECM-IAIDS	T1	16.01***	2.98	2.64	15.67***	18.65***
	T2	15.45***	2.98	2.64	15.12***	18.06***
	T3	2.78**	0.18	2.59*	2.64**	2.65**
	T4	7.67*	0.55	7.78*	7.91**	7.94
	Critical values					
	df	0.1		0.05		0.01
λ^2	3	6.2513		7.8147		11.3448
	6	10.6446		12.5915		16.8118
F	3	2.0838		2.6049		3.782
	6	1.7741		2.0986		2.802

Note: * p<0.1, ** p<0.05, and *** p<0.01; Degree of freedom is in parenthesis.

For the whole sample, T_1 and T_2 both reject the null hypothesis that homogeneity or both homogeneity and symmetry restrictions hold, while T_3 and T_4 cannot reject these two restrictions at the 1% confidence level. These results are consistent with previous studies using the same statistics (Deaton 1972; 1974).

Table 4-8 also shows that the ECM-IAIDS model performs better than the IAIDS model. However, the robustness of the ECM-IAIDS model should be checked by testing its forecasting ability. To do this, the general ECM model is used by treating all prices, quantities and expenditures endogenous. Since both homogeneity and symmetry restrictions cannot be rejected in the ECM-IAIDS model according to test statistics T_3 and T_4, I compare forecasting results of the ECM-IAIDS model with both homogeneity and symmetry imposed and the general ECM model without any restrictions.

4.5.3 Forecasts Evaluation

As indicated above, the robustness of the ECM-IAIDS model should be checked because of the weakly exogenous assumption of quantities and expenditure. Using two subsamples estimated above, I predict one-step ahead forecast for the rest of the data, i.e. from November 2003 to December 2010 and from August 2006 to December 2010, respectively. The same procedure is applied to the general ECM model. According to previous studies (Kastens and Brester 1996; Klaiber and Holt 2010; Wang 2010), models are evaluated by two approaches--the root mean squared forecast errors (RMSFE) and the encompassing tests following Chong and Hendry (1986) and Wang and Bessler (2003).

The compassing tests require that the following estimation,

$$(4.13)\quad e_{it} = \Gamma(e_{it} - e_{jt}) + \varepsilon_{it}$$

where e_{it} and e_{jt} represents forecast errors from model i and j, respectively. I test the null hypothesis of model i encompasses model j by testing $\Gamma = 0$. A t test or a LR test statistics could be used to perform the test. A significant p-value indicates that the forecasts generated from model i and model j are different and do not encompass each other (Klaiber and Holt 2010).

Table 4-9 RMSFE and Statistics on Encompassing Tests

	2003m11-2010m12			2006m8-2010m12		
	Beef	Pork	Chicken	Beef	Pork	Chicken
ECM	0.0037	0.0046	0.0034	0.0036	0.0040	0.0027
ECM-IAIDS	0.0056	0.0034	0.0051	0.0064	0.0037	0.0047

Tests of Two-way Encompassing

	Coefficient	Test statistics	Coefficient	Test statistics
ECM encompasses ECM-IAIDS	0.4060	F(1,256)=181.14 Prob>F=0	0.3160	F(1,157)=67.17 Prob>F=0
ECM-IAIDS Encompasses ECM	0.5939	F(1,256)=387.71 Prob>F=0	0.6840	F(1,157)=314.76 Prob>F=0

Note: I did the following transformation of forecast values to get the forecast budget share of $\hat{w}_t = \exp(\ln \hat{p}_t + \ln \hat{q}_t - \ln \hat{\exp}_t)$, where $\ln \hat{p}$, $\ln \hat{q}$ and $\ln \hat{\exp}_t$ are one-step ahead forecast value from the ECM model.

Table 4-9 reports the RMSFE and statistics on the encompassing tests. In both subsamples, ECM performs better for the beef and chicken forecasting, while the ECM-IAIDS model fits the data better for the pork equation. The encompassing test results also show that the ECM and the ECM-IAIDS models are different and cannot encompass each other. In other words, the ECM-IAIDS model proposed in this study is also important to capture the meat consumption pattern in the United States. Figure 4-4 and Figure 4-5 shows predicted and observed values for two subsamples, respectively.

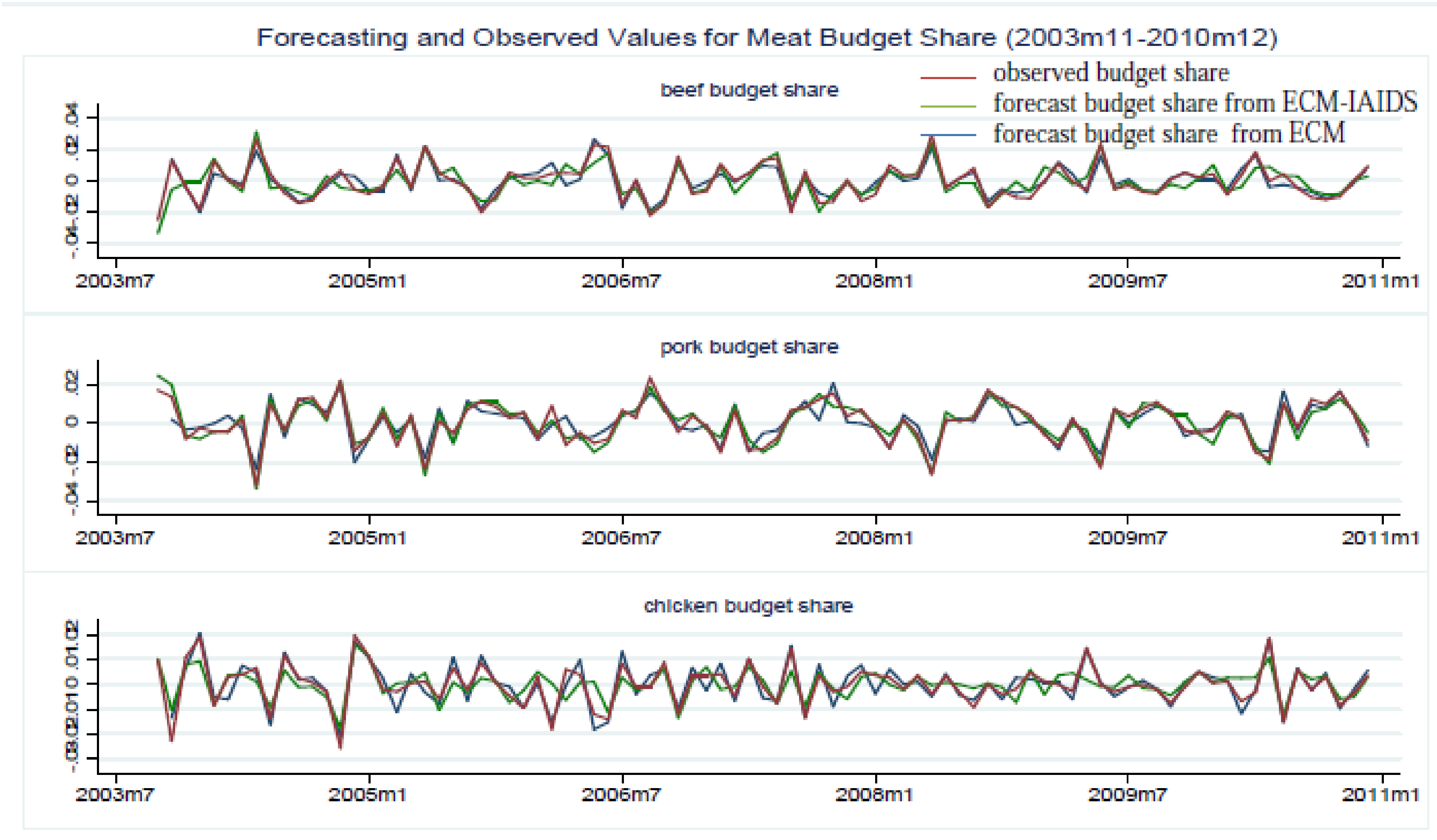


Figure 4-4 Forecasted and Observed Budget Share from 2003m11 to 2010m12

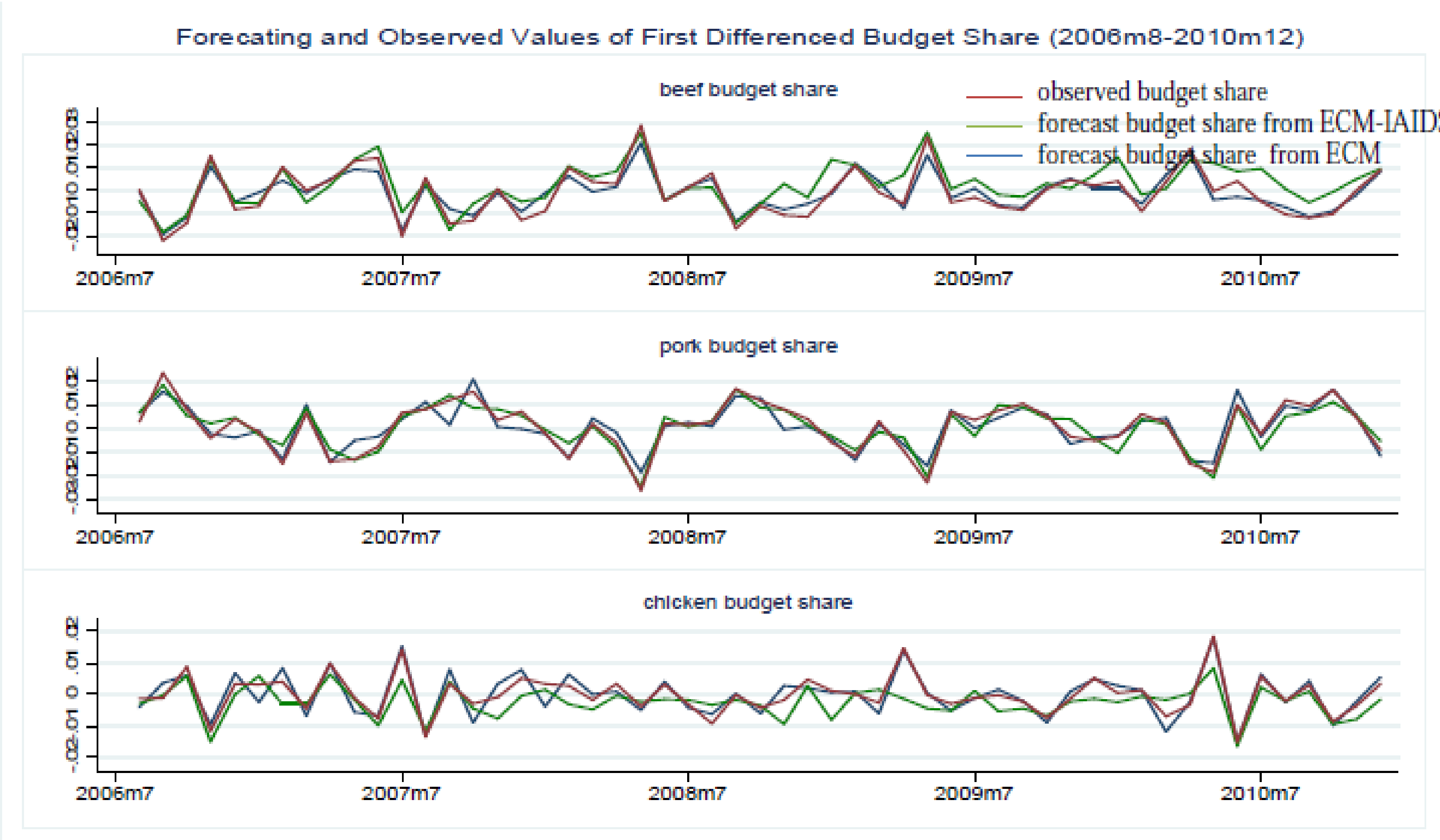


Figure 4-5 Forecasted and Observed Budget Share from 2006m8 to 2010m12

4.6 Concluding Remarks

In this paper, I analyze the economic impacts of animal disease information on meat consumption in the United States using the error corrected inverse almost ideal demand model (ECM-IAIDS).

By testing time series properties of demand data, I find that employing a dynamic demand model is appropriate. Examining the ECM-IAIDS model, results find that in short run, people react more to nearby disease outbreaks than to those that occurred overseas, whereas in long run, all information related to animal disease outbreaks will influence consumers' consumption patterns. Although the economic influences of animal disease on meat consumption are statistically significant, they are economically small.

Based on restriction tests and forecast evaluation, results show that the ECM-IAIDS model fits the data better. In particular, both homogeneity and symmetry restriction hold for subsamples based on alternative test statistics proposed by Deaton (1972; 1974). From a comparison with the benchmark ECM model, which is usually considered as the superior model in forecasting (Wang and Bessler 2003), results of RMSFE and the encompassing test statistics both present that the ECM model cannot encompass the ECM-IAIDS model. In other words, both models are important in forecasting.

5. EVALUATION OF AI MITIGATION STRATEGIES[29]

5.1 Introduction

The prevalence of outbreaks of AI in Asia, Europe and Africa and their economic consequences raise concerns about prevention methods, mitigation options and their cost effectiveness. Referring to the United States, several AI strains caused outbreaks among poultry during 2003 and 2004 (H7N2 in New York in 2003, and Delaware, New Jersey and Maryland in 2004; H5N2 in Texas in 2004), all of which caused large losses to farmers as well as in exports of poultry and/or poultry products as revealed in Section 2.

Historically, the 1993-1994 outbreaks of LPAI in Pennsylvania resulted in depopulation of over 17 million birds and cost the federal government over $60 million (Akey 2003). The 1983-1984 AI outbreaks cost $63 million and a 2002 case led to a producers' loss of between $130 and $140 million (Cupp et al. 2004). More recently, a HPAI strain was diagnosed in Gonzales County, Texas in a flock of infected broiler chickens in February 2004, which involved a broiler farm of 6 thousand birds plus 5 live bird markets. Subsequently, 44 countries banned imports from either Texas or United States-originated poultry or poultry products (Pelzel et al. 2006). The overall value of all poultry and poultry products produced and exported from Texas was $123 million, which represented 5.4% of the total value of U.S. poultry and poultry product in 2002.

[29] This section is extended based on Egbendewe (2009)'s dissertation. Please refer to Egbendewe (2009) for background information.

Although there has been no large AI outbreak in the United States since 2004, planning of mitigation strategies is important for preventing a potential outbreak of AI and for reducing the economic costs of future outbreaks. AI outbreaks are unpredictable as most poultry producing regions are on wild bird flyways and evidences show that wild birds' migration can spread the disease (European Food Safety Authority 2006).

This study simulates an AI outbreak in the United States and evaluates two mitigation strategies -- quarantine and vaccination. By using epidemic and economic models, this study examines how a large AI outbreak assumed in the United States would affect production and welfare by alternative AI mitigation strategies considering not only the domestic demand shock, but also a potential international demand shift. In pursuing of the objective, this study

- Uses a susceptible, latent, infected and removed epidemic model developed by Egbendewe (2009) to simulate the loss of the poultry population in the United States
- Incorporates the simulated production outcomes plus domestic demand and international trade responses into a U.S. Agricultural Sector Model (Adams et al. 2005)
- Uses the linked economic and epidemic model to simulate the production, price and welfare changes under two alternative mitigation strategies

This essay is organized as follows. Section 5.2 discusses the economic intuition; section 5.3 reports design of this study; section 5.4 presents results; section 5.5 examines the ex-post evaluation of AI outbreak costs due to paste climate change and section 5.6 provides conclusions and policy implications.

5.2 Economic Intuition

In this section, a theoretical model is discussed to reveal the underlying economic meaning of this study. Assuming an AI outbreak occurs nationally in the United States and spreads to other flocks in each region with the same contact rate as surveyed in Texas by Egbendewe (2009).

Theoretically, the AI outbreak causes depopulation of chicken if vaccination is not implemented. Figure 5-1 shows the case with supply shock. Domestic demand and export demand also shrinks because people become more cautious of consuming poultry products when receiving a large number of media coverage of AI outbreaks all over the world. Sequentially, national prices and welfares are impacted due to those effects. However, changes vary when different AI mitigation strategies are implemented and the biggest difference is depending on how large the supply and demand curves shift. Figures 5-2, 5-3 and 5-4 show changes of price, production quantity and welfare under three cases of demand shocks without vaccination.

- If only domestic demand is affected negatively, and the magnitude is smaller than the shift of supply, then both price and production quantity will go down slightly. Therefore, producers' surplus decreases and consumers' surplus is uncertain if vaccination is not used

- If only excess demand shock is included, price will go down significantly, consumer surplus increases and producer surplus declines under no vaccination strategy
- If both domestic and excess demand is affected, price and production quantity will go down significantly, producer surplus declines but consumer surplus is unclear

This essay assumes the effect of the AI outbreak on supply is negligible if vaccination strategy is applied. Therefore, Figures 5-2, 5-3 and 5-4 could also present the situation with vaccination.

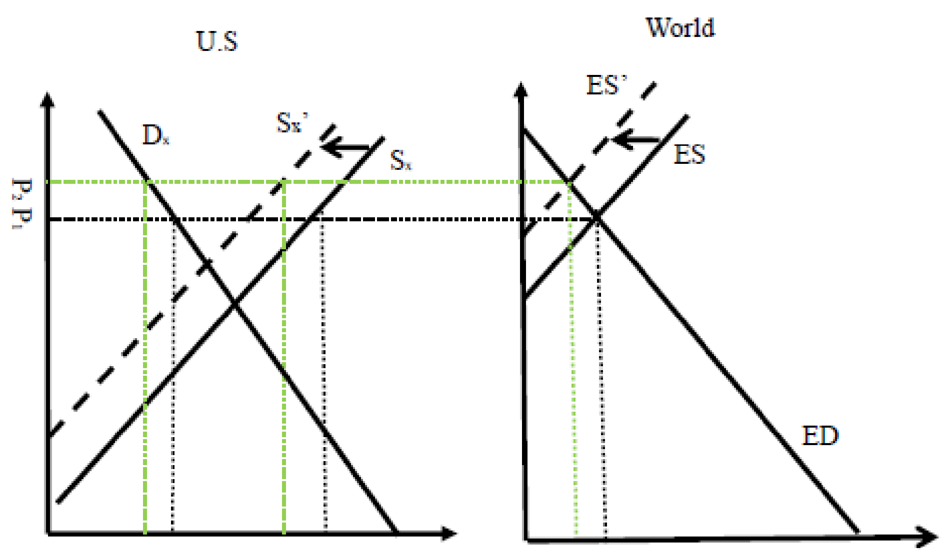


Figure 5-1 Changes in Price and Production under Supply Shock

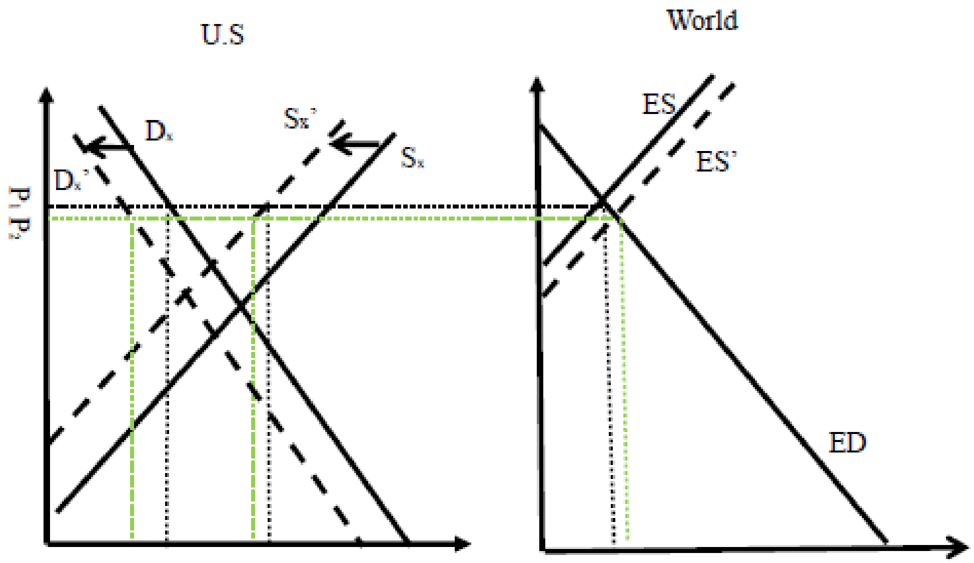


Figure 5-2 Changes in Price and Production under Domestic Demand Shock

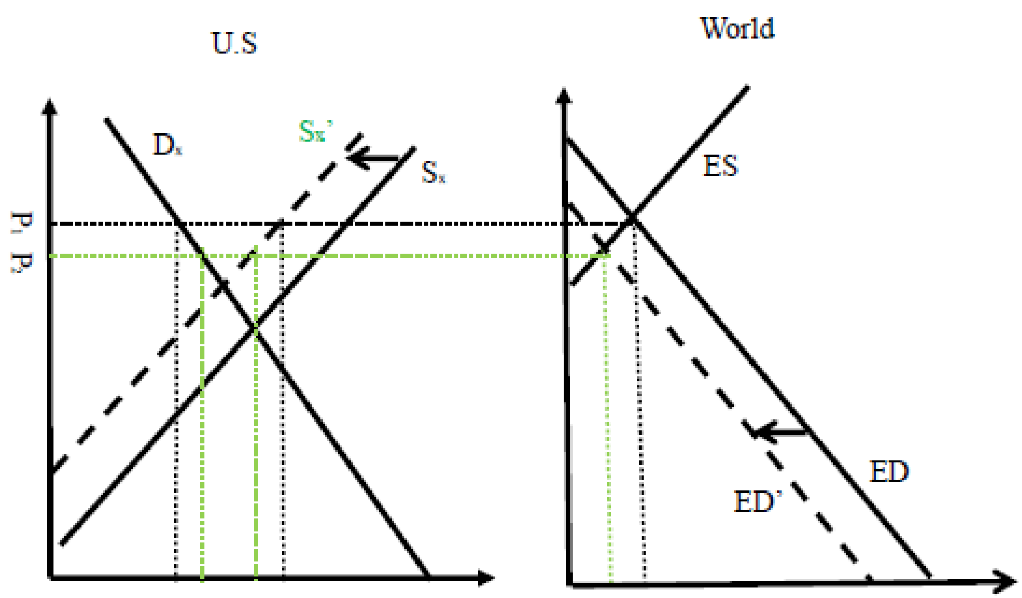


Figure 5-3 Changes in Price and Production under Excess Demand Shift

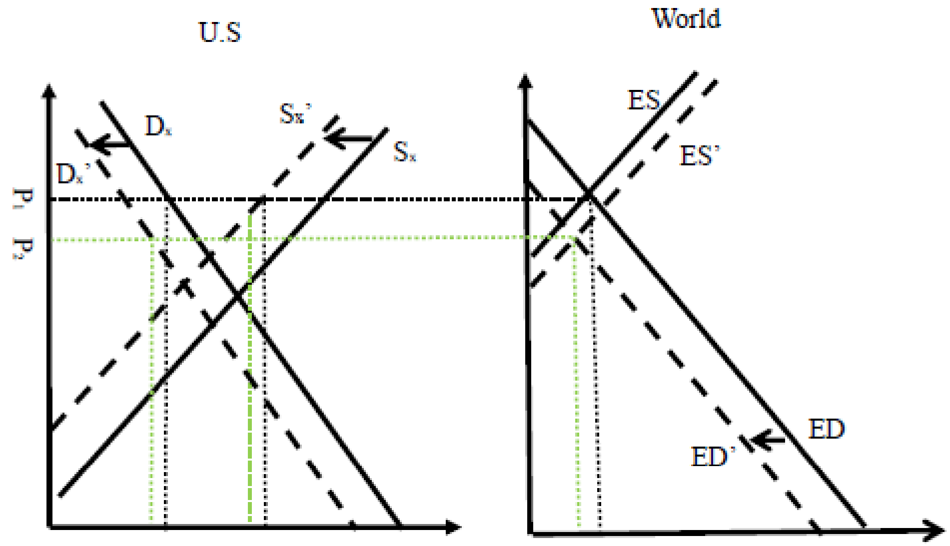


Figure 5-4 Changes in Price and Production under Both Demand Shifts

5.3 Study Design

Based on theoretical models, there are three steps to integrate the epidemic model and economic model to examine AI mitigation strategies under alternative demand shifts. These steps includes,

- Constructing Scenarios
- Making appropriate adjustments in epidemic model to reflect economic questions

- Making necessary conversions for the epidemic model output to become the economic model input and make appropriate adjustments in the economic model

5.3.1 Scenario Constructions

The first step before starting an integrated economic/epidemic study is to determine the focus and scope of the region to be depicted plus the nature of the disease outbreak and possible control strategies (Hagerman 2009).

5.3.1.1 Research regions

Assuming there is a national outbreak of AI which could hurt the poultry industry in the United States, especially for states have a high proportion of poultry production, such as Alabama, Arkansas, Georgia, Kentucky, Mississippi, North Carolina and Texas. As shown in Figure 5-5, Alabama (11%), Arkansas (13%), Georgia (16%), Kentucky (3%), Mississippi (9%), North Carolina (9%) and Texas (7%) produce a large share of U.S. broiler production, and the total is around 68%. Also shown in Table 5-1, these selected regions produce 22% of U.S. egg production and 25% of U.S. turkey production. Thus, mainly these seven regions are included in this study.

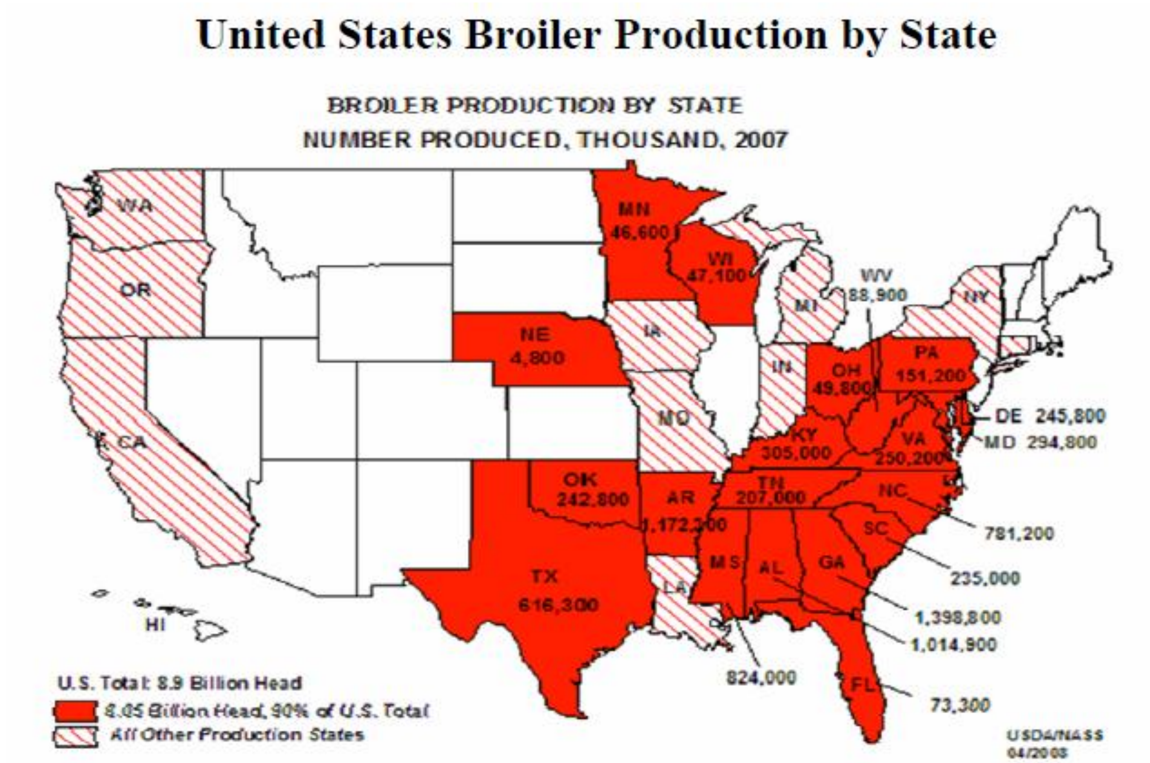


Figure 5-5 Inventory of Broiler Production in 2007

In addition, I also consider the shock on U.S. exports of poultry meat or products due to the AI outbreak. AI is one of the epidemic diseases that can spread quickly within birds and its outbreak in the United States could also affect international demand since people in other countries are afraid of eating poultry products. The United States is the world's largest producer and second largest exporter of poultry meat. In 2007, poultry production meat was over 36 billion pounds and the total farm value of U.S. poultry production exceeded $22 billion. Meanwhile, broiler exports were about 12% of production with 5.9 billion pounds exported, valued at $2.7 billion.

Table 5-1 Proportion of Productions in Selected Regions

Regions	Broiler		Egg		Turkey	
	Production (million head)	Percent (%)	Production (million)	Percent (%)	Production (million head)	Percent (%)
Alabama	1023	11	2090	2		
Arkansas	1176	13	3236	4	30	11
Georgia	1399	16	4792	5		
Kentucky	303	3	1170	1		
Mississippi	824	9	1523	2		
North Carolina	781	9	2960	3	39	14
Texas	616	7	4995	5		
Regional Total	6122	68	20766	22	69	25
U.S.	8907	100	91101	100	267	100

Source: U.S. Agriculture Census of 2007.

5.3.1.2 Intervention strategies

As stated in Section 2, there are two disease control options in the AI context, one is a quarantine strategy and the other is the vaccination strategy. The former recommends establishing a quarantine strategy zone in a 5-miles radius around the outbreak site within which every flock is depopulated, and then a varying surveillance radius around that zone plus movement restrictions and testing (Pelzel et al. 2006). The vaccination strategy suggests vaccinating all susceptible flocks in near proximity to the quarantine zone in addition to the quarantine strategy stated above in terms of reducing the probability of infection and the amount of virus produced by an infected flock (FAO 2004).

Both strategies depend on the probability of an AI outbreak, the densities of poultry flocks and the contact rate between different poultry flocks. Therefore, the decision of choosing the quarantine or vaccination response is determined by the expected economic costs of a potential AI outbreak.

To poultry producers, vaccination is a risk investment strategy. If the probability of an AI outbreak is low, vaccination will increase their management costs; In return, produces will face less loss if the probability of an AI outbreak is high. Meanwhile, producers are also affected by demand shifts as the reason discussed in Section 4. Thus, the cost-effectiveness of mitigation strategies depends not only on intervention strategies, but also on demand changes from domestic and international market due to the AI outbreak.

5.3.1.3 Scenarios

In general, a “base” scenario runs the integrated simulation model once for no disease incursion. This makes the assessment of alternative scenarios more meaningful in that there is a frame of reference from which to compare (Hagerman 2009). Although in Section 4, I estimated the impacts of AI media information on chicken demand in the United States would decline by 0.25 %, a more serious case of 5% demand shock and a lighter case of no demand shock are both considered for sensitivity analysis. Therefore, 8 scenarios are constructed regarding to different intervention options and demand shocks as shown in Table 5-2.

Table 5-2 Scenarios Constructed in ASM

	Intervention		Domestic demand shift		Excess demand shift	
Scenario	No vaccination	Vaccination	0%	5%	0%	5%
1	X		X		X	
2	X			X	X	
3	X		X			X
4	X			X		X
5		X	X		X	
6		X		X	X	
7		X	X			X
8		X		X		X

5.3.2 Epidemic Modeling

The second stage in doing integrated disease modeling is to estimate the animal loss, degraded performance and extent of the control effect caused by the disease using principles of epidemiology. This is typically done using an epidemic model (Hagerman 2009).

5.3.2.1 Epidemic SLIR model

Few studies of AI mitigation strategies have been done partly because limited availability of epidemic or statistical models within which the consequences of strategies can be simulated. Previous studies of animal disease suggest that studies which contain more through integration of economic and epidemic models would improve the analysis quality (Paarlberg et al. 2005; Pritchett et al. 2005).

In an AI context, Elbakedze (2008) presents a largely theoretical model that depicts AI mitigation options within the small poultry farm sector (backyard flocks) by incorporating epidemiologic susceptible-infected-recovered (SIR) model into an economic cost-minimization framework, but does not integrate price response or a very comprehensive framework ignoring feed effects and possible adjustments in production of substitute meat. In a following study, Egbendewe (2009) constructs a SLIR model based on farm survey data, examines the use of vaccination to control an AI outbreak in Texas, and finds that vaccination dominates non-vaccination. This study follows Egbendewe (2009) extending the model to a national basis.

Egbendewe (2009)'s AI epidemic analysis is based on the SLIR model. In each time period, individual farms are assumed to be in one of the four stages of the disease progression. Those stages are susceptible (S), latent infectious (L), symptomatic infectious (I) and removed (R). If vaccination is utilized during the outbreak period, the vaccinated farms are immune and are therefore subtracted out each period from the susceptible farms because they are not vulnerable to the disease. This implies that vaccinated flocks would not need to go through the latent and the infected stages (Egbendewe 2009). Thus, by the end of the period, for example 30 days or more, there is a proportion of bird category at each stage.

Both Elbakidze (2008) and Egbendewe (2009) studies were limited in geographic scope and in the markets considered. Once there was an AI, its effects would not necessarily be confined to the domestic market, it could reach international market through media coverage (Beach and Zhen 2008), so I will use an economic sector model, which could take care of not only the domestic supply and demand shock, but also the international demand shift. To achieve this, I use the epidemic model to feed data into a sector model.

Table 5-3 Number of Farms in Selected Regions

Regions	Layersl	Layerss	Broiler	Turkey	Backyards	Total
Alabama	7	446	2263	279	1964	4959
Arkansas	5	543	2408	530	2499	5985
Georgia	35	494	2170	350	2341	5390
Kentucky	3	106	909	434	4020	5472
Mississippi	3	215	1478	203	1707	3606
North Carolina	8	452	1879	846	3266	6451
Texas Central Black	10	54	395	235	1526	2220
Texas East	6	111	923	282	1847	3169
Total	77	2421	12425	3159	19170	37252

Source: U.S. Agriculture Census of 2007.

Table 5-4 Infected and Latent Daily Contact Rate

	Layersl	Layerss	Broiler	Turkey	Backyard
			Infected daily contact rates		
Layersl	2.93	2.87	2.87	2.87	2.87
Layerss	2.87	2.93	2.87	2.87	2.87
Broiler	0.57	0.57	0.61	0.57	0.57
Turkey	1.29	1.29	1.19	1.3	1.29
Backyard	2.87	2.87	2.87	2.87	2.93
			Latent daily contact rates		
Layersl	0.06	2.87	2.87	2.87	2.87
Layerss	2.87	0.06	2.87	2.87	2.87
Broiler	0.57	0.57	0.57	0.57	0.57
Turkey	1.29	1.29	1.19	0.01	1.29
Backyard	2.87	2.87	2.87	2.87	0.06

Source: : Egbendewe (2009).

5.3.2.2 Data for the SLIR model

Based on the U.S. Agriculture Census of 2007, poultry farms in each affected region can be categorized into five types of farms as follows:

- Large size layers operations of more than 100,000 birds (layersl)
- Small size layers operations between 400 birds to 100,000 birds (layerss)
- Backyard operations of layers less than 400 birds (backyards)
- Broiler operations (broiler)
- Turkey operations (turkey)

The total number of farms in each affected regions is given in Table 5-3. I assume that infected and latent daily contact rate across these regions for individual flocks are those found in the Texas survey by Egbendewe (2009), which could be found in Table 5-4. The only difference between infected and latent daily contact rate is that the contact rate between the same categories is much smaller in latent flocks.

I calculate the probability of disease transmission between flocks using

$\frac{\text{Contact Rate}}{N-1}$, where N is the number of farms of each flock in each region. Table 5-5 gives the probability of AI disease transmission from infected and latent flocks. In all selected regions, transmission probability is relatively high between layers to layers and backyards, but relatively low from layers to broiler and turkey.

Table 5-5 Probability of Disease Transmission in Affected Regions

	Layersl	Layerss	Broilers	Turkey	Backyard	Layersl	Layerss	Broilers	Turkey	Backyard
					Transmission probability from infected flocks					
	Alabama					Mississippi				
Layersl	0.4883	0.0064	0.0013	0.0103	0.0015	1.4650	0.0134	0.0019	0.0142	0.0017
Layerss	0.4783	0.0066	0.0013	0.0103	0.0015	1.4350	0.0137	0.0019	0.0142	0.0017
Broilers	0.0950	0.0013	0.0003	0.0021	0.0003	0.2850	0.0027	0.0004	0.0028	0.0003
Turkey	0.2150	0.0029	0.0005	0.0047	0.0007	0.6450	0.0060	0.0008	0.0064	0.0008
Backyard	0.4783	0.0064	0.0013	0.0103	0.0015	1.4350	0.0134	0.0019	0.0142	0.0017
	Arkansas					North Carolina				
Layersl	0.7325	0.0053	0.0012	0.0054	0.0012	0.4186	0.0064	0.0015	0.0034	0.0009
Layerss	0.7175	0.0054	0.0012	0.0054	0.0012	0.4100	0.0065	0.0015	0.0034	0.0009
Broilers	0.1425	0.0011	0.0003	0.0011	0.0002	0.0814	0.0013	0.0003	0.0007	0.0002
Turkey	0.3225	0.0024	0.0005	0.0025	0.0005	0.1843	0.0029	0.0006	0.0015	0.0004
Backyard	0.7175	0.0053	0.0012	0.0054	0.0012	0.4100	0.0064	0.0015	0.0034	0.0009
	Georgia					Texas central black				
Layersl	0.0862	0.0058	0.0013	0.0082	0.0012	0.3256	0.0542	0.0073	0.0123	0.0019
Layerss	0.0844	0.0059	0.0013	0.0082	0.0012	0.3189	0.0553	0.0073	0.0123	0.0019
Broilers	0.0168	0.0012	0.0003	0.0016	0.0002	0.0633	0.0108	0.0015	0.0024	0.0004
Turkey	0.0379	0.0026	0.0005	0.0037	0.0006	0.1433	0.0243	0.0030	0.0056	0.0008
Backyard	0.0844	0.0058	0.0013	0.0082	0.0013	0.3189	0.0542	0.0073	0.0123	0.0019
	Kentucky					Texas East				
Layersl	1.4350	0.0279	0.0032	0.0066	0.0007	0.5740	0.0266	0.0031	0.0102	0.0016
Layerss	0.2850	0.0054	0.0007	0.0013	0.0001	0.1140	0.0052	0.0007	0.0020	0.0003
Broilers	1.4650	0.0273	0.0032	0.0066	0.0007	0.5860	0.0261	0.0031	0.0102	0.0016

Table 5-5 Continued

	Layersl	Layerss	Broilers	Turkey	Backyard	Layersl	Layerss	Broilers	Turkey	Backyard
Turkey	0.6450	0.0123	0.0013	0.0030	0.0003	0.2580	0.0117	0.0013	0.0046	0.0007
Backyard	1.4350	0.0273	0.0032	0.0066	0.0007	0.5740	0.0261	0.0031	0.0102	0.0016
				Transmission probability from latent flocks						
	Alabama					Mississippi				
Layersl	0.0100	0.0064	0.0013	0.0103	0.0015	0.0300	0.0134	0.0019	0.0142	0.0017
Layerss	0.4783	0.0001	0.0013	0.0103	0.0015	1.4350	0.0003	0.0019	0.0142	0.0017
Broilers	0.0950	0.0013	0.0003	0.0021	0.0003	0.2850	0.0027	0.0004	0.0028	0.0003
Turkey	0.2150	0.0029	0.0005	0.0000	0.0007	0.6450	0.0060	0.0008	0.0001	0.0008
Backyard	0.4783	0.0064	0.0013	0.0103	0.0000	1.4350	0.0134	0.0019	0.0142	0.0000
	Arkansas					North Carolina				
Layersl	0.0150	0.0053	0.0012	0.0054	0.0012	0.0086	0.0064	0.0015	0.0034	0.0009
Layerss	0.7175	0.0001	0.0012	0.0054	0.0012	0.4100	0.0001	0.0015	0.0034	0.0009
Broilers	0.1425	0.0011	0.0002	0.0011	0.0002	0.0814	0.0013	0.0003	0.0007	0.0002
Turkey	0.3225	0.0024	0.0005	0.0000	0.0005	0.1843	0.0029	0.0006	0.0000	0.0004
Backyard	0.7175	0.0053	0.0012	0.0054	0.0000	0.4100	0.0064	0.0015	0.0034	0.0000
	Georgia					Texas central black				
Layersl	0.0018	0.0058	0.0013	0.0082	0.0012	0.0067	0.0542	0.0073	0.0123	0.0019
Layerss	0.0844	0.0001	0.0013	0.0082	0.0012	0.3189	0.0011	0.0073	0.0123	0.0019
Broilers	0.0168	0.0012	0.0003	0.0016	0.0002	0.0633	0.0108	0.0014	0.0024	0.0004
Turkey	0.0379	0.0026	0.0006	0.0000	0.0006	0.1433	0.0243	0.0030	0.0000	0.0008
Backyard	0.0844	0.0058	0.0013	0.0082	0.0000	0.3189	0.0542	0.0073	0.0123	0.0000
	Kentucky					Texas East				
Layersl	0.0300	0.0273	0.0032	0.0066	0.0007	0.0120	0.0261	0.0031	0.0102	0.0016

Table 5-5 Continued

	Layersl	Layerss	Broilers	Turkey	Backyard	Layersl	Layerss	Broilers	Turkey	Backyard
Layerss	1.4350	0.0006	0.0032	0.0066	0.0007	0.5740	0.0005	0.0031	0.0102	0.0016
Broilers	0.2850	0.0054	0.0006	0.0013	0.0001	0.1140	0.0052	0.0006	0.0020	0.0003
Turkey	0.6450	0.0123	0.0013	0.0000	0.0003	0.2580	0.0117	0.0013	0.0000	0.0007
Backyard	1.4350	0.0273	0.0032	0.0066	0.0000	0.5740	0.0261	0.0031	0.0102	0.0000

Source: Egbendewe (2009) but edited by the author.

5.3.2.3 Results from the SLIR model

Using the data from Table 5-5, I simulate the situation after a time period, for example 30 days, to see the proportion of each flock at each stage. Figure 5-6 reports results from the SLIR model, which I will put into ASM to examine welfare changes of two AI mitigation strategies under different demand shocks.

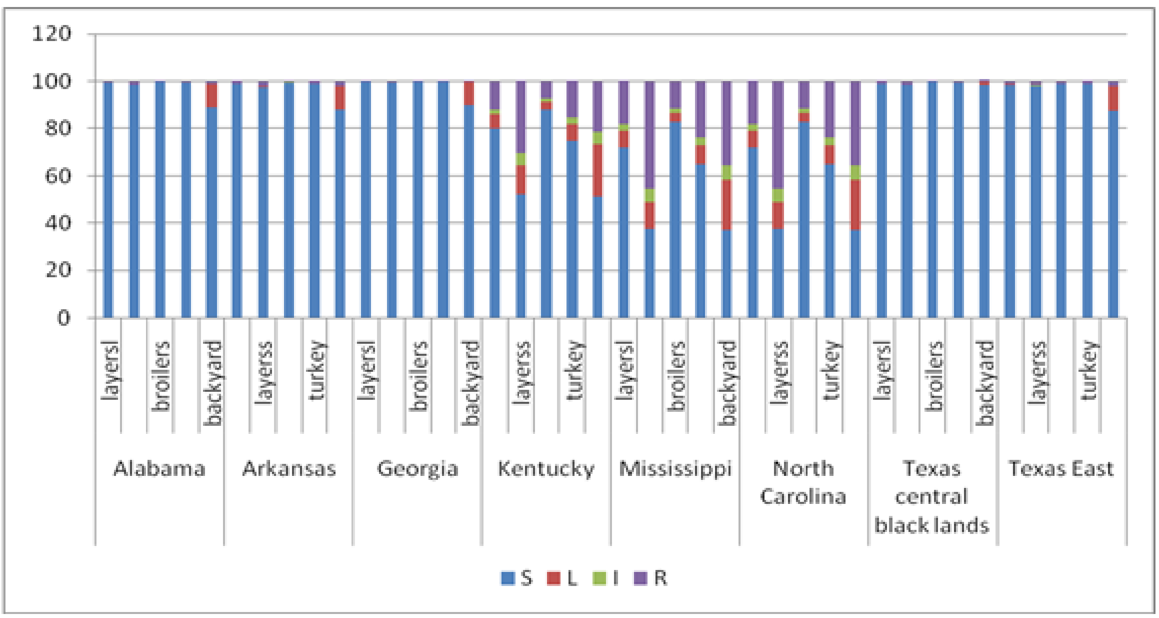


Figure 5-6 Proportions of Each Stage of Flocks in Selected Regions

In all affected regions, It could be seen that backyards have a high proportion of the latent stage as well as the removed stage. Kentucky, Mississippi and North Carolina are affected seriously with a higher proportion of poultry removed. In other regions, impacts of AI outbreaks after 30 days are not significant.

5.3.3 Economic Modeling

The third stage is the bridging of the epidemic and economic models and the disease related adjustments in the economic model (Hagerman 2009). A sector model is used here in conjunction with the Epidemic model to depict the welfare and market responses associated with an assumed AI outbreak.

5.3.3.1 ASM model

The ASM is incorporated in the Forest and Agricultural Sector Optimization Model (FASOM). ASM and FASOM are dynamic and nonlinear programming models that were developed to evaluate the welfare and market impacts of public policies that cause land transfers between the sectors and resource reallocation involving alterations of activities within the sectors (Adams et al. 2005). ASM is a spatially disaggregated agricultural sector model representing the United States in terms of 63 production regions and 10 market regions depicting trade with a number of foreign countries and it also depicts production in an equilibrium year and is thus an intermediate run model giving implications for policy after it has been fully worked into the sector (Adams et al. 2005).

More importantly, ASM is a partial equilibrium model and its advantage is to allow price to be endogenous. The assumption of price is very important. If price is exogenous, as in Egbendewe (2009)'s study, it limits the impacts of an AI outbreak to the study region. However, if allowing price changes along with demand and supply, price and quantity of poultry could change, so a regional outbreak could affect producer's welfare nationally through the product and factor markets. Based on this fact, it is more realistic to let price be endogenous and that is why ASM is used in this essay.

In implementing an animal disease, the focus will be on reducing the production of outputs and increasing other costs. This will imitate a "disease shock" on the region of interest. Budgets in ASM are normalized to a one animal basis. This means epidemic data in terms of head slaughtered, vaccination, or restricted must also be normalized. Intuitively, the impact of the disease is spread evenly across an entire region such that the average productivity per animal in the region is reduced and the average cost of production per animal is increased. Because of the supply and demand relationships in the model, an animal disease shock impact assessment can occur both upstream and downstream of the actual livestock production budgets (Hagerman 2009).

5.3.3.2 Data for the ASM model

Since ASM only includes eggs rather than layers, It is needed to transfer production of layers to production of eggs. Table 5-6 presents percentage of layer production for each category. When constructing or altering model data, I need to map each layer category into egg production and adjust the livestock production budget, feed use and management costs of eggs rather than layers.

Table 5-6 Percentage of Layer Production in Selected Regions

Regions	Layerss	Layersl	Backyards
Alabama	0.8285	0.1668	0.0047
Arkansas	0.7377	0.2583	0.0040
Georgia	0.5248	0.4724	0.0029
Kentucky	0.9121	0.0654	0.0225
Mississippi	0.9449	0.0481	0.0070
North Carolina	0.6850	0.3085	0.0065
Texas	0.2616	0.7224	0.0160
Total	0.6102	0.3817	0.0081

Source: U.S. Agriculture Census of 2007.

Management costs in this study include surveillance cost, cost of disposal, vaccination cost and cost of labor, all of which are measured in unit and are obtained from different sources. Table 5-7 shows details of each cost and source.

Table 5-7 Management Costs and Sources

Costs	Category	Cent/bird	Source
Surveillance	20 birds in each farm	15	Texas AI response document (2006)
Carcass disposal	Layersl	0.008	Egbendewe (2009)
	Layerss	0.006	
	Broiler	0.006	
	Turkey	0.004	
	Backyard	0.002	
Vaccination	All birds	0.012	CIDRAP (2005); Smith (2007)
Labor	All birds	0.038	Egbendewe(2009)

Source: Egbendewe (2009) but edited by the author.

5.3.3.3 Adjustments performed in the ASM model

Herd types in ASM impacted by AI are broilers, eggs (layersl, layerss, and backyard) and turkey. Therefore, it needs to adjust budget constraints individually.

The number of adults in the broiler, layers and turkey herd is adjusted to reflect reactions due to the death of directly infected, indirect contacts due to quarantine policy and the removed of infected animals.

The following equations show the adjustments made for this study and these adjustments are corresponding to each flock, particularly,

(5.1) $$LB\_Broiler_{\mathrm{Re}g,Type,Animal} = LB\_Broiler_{\mathrm{Re}g,Type,Animal} * (1 - Perc\_Change)$$

(5.2) $$LB\_Eggs_{i,\mathrm{Re}g,Type,Animal} = LB\_Eggs_{i,\mathrm{Re}g,Type,Animal} * (1 - Perc\_Change)$$

(5.3) $$LB\_Turkey_{\mathrm{Re}g,Type,Animal} = LB\_Turkey_{\mathrm{Re}g,Type,Animal} * (1 - Perc\_Change)$$

where

$LB\_Broiler$ is the pounds of poultry meat produced by a broiler

LB_Eggs_i is the numbers of eggs produced by a layer, i indicates different type of layers in this study including layersl, layerss and backyard

$LB\_Broiler$ is the pounds of turkey meat produced by a turkey

Reg is the region of infection

Type is the type of budget being adjusted including production, management costs and feed inputs

Animal is the output of the budget being adjusted

$Perc\_Change$ is the percentage of disease loss in the infection region

After making these adjustments, I run the ASM model to get economic results including national welfare, price and production, producers' surplus and regional consumers' and producers' surplus.

5.4 Results

The ASM Model has several benefits in terms of examining multiple areas impacted by the disease shock. The impact categories discussed below are the areas that have been used most intensively for this animal disease analysis (Hagerman 2009).

5.4.1 Changes in National Welfare

Welfare change is a measure of economic gain/loss that is more encompassing than loss measures like GDP or disease mitigation cost (Paarlberg et al. 2008) and useful in determining the impact of policy changes and disease shocks (Rich et al. 2005). ASM shows changes in total national agricultural welfare from the baseline of no disease and breaks those changes down by domestic agriculture producers, consumers and processors and it also examines changes in welfare for foreign producers, consumers and processors (Hagerman 2009).

In this study, I focus on changes in total U.S. welfare from agriculture. Table 5-8 shows the national welfare changes from the base and concludes that national welfare is reduced because of the AI outbreak.

Table 5-8 National Welfare and Loss from the Base under Demand Shifts

	No vaccination			Vaccination		
	Mean (billions)	95% C.I. [lower, upper]		Mean (billions)	95% C.I. [Lower, upper]	
			Base			
National welfare (billion)	1463.82			1463.82		
			No demand shift			
National welfare (billion)	1461.33	1461.2	1463.75	1447.96	1447.16	1463.4
Loss from the base	-2.49			-15.86		
			5% domestic demand shift			
National welfare (billion)	1412.44	1375.05	1463.6	1398.77	1360.68	1463.25
Loss from the base	-51.38			-65.05		
			5% excess demand shift			
National welfare (billion)	1460.99	1460.68	1463.75	1447.63	1446.65	1463.4
Loss from the base	-2.83			-16.19		
			5% domestic & excess demand shift			
National welfare (billion)	1411.96	1374.15	1463.6	1398.29	1359.77	1463.25
Loss from the base	-51.86			-65.53		

Note: C.I. indicates the confidence interval.

Without demand shock, national welfare will decline by \$2.49 billion if no vaccination is used and \$15.86 billion if vaccination is used. With 5% domestic demand shift, national welfare will decrease by \$51.38 billion and \$65.05 billion without and with vaccination, respectively.

With 5% excess demand shift, national welfare losses are close to the case without demand shift and they are reduced by \$2.83 and \$16.19 billion under two intervention strategies, respectively. If domestic and excess demand both shifts by 5%, national welfare declines more, by $51.85 billion without vaccination and $65.53 with vaccination.

It can be seen that situations are even worse if vaccination is used. From Figures 5-1 to 5-4, it seems that changes in price and quantities determine whether vaccination is cost effective or not. Empirical results show that vaccination is not cost effective under all demand shifts.

5.4.2 Changes in Producers' Surplus

Only examining the changes in total U.S. agricultural producers welfare may mask the fact that some regions' producers will be face more losses than other regions. In fact, some regions producers who are not directly infected could potentially gain from the outbreak (Hagerman 2009). To examine these, dynamic producers' surplus is examined on a national and sub-regional basis.

5.4.2.1 National producers' surplus

When looking at producers' welfare at a national level, results are consistent with changes in national welfare with producers lose more under demand shocks. Table 5-9 reports changes in total producers' surplus from the base under different demand shocks. If there is no demand shock, producers gain $1.38 billion without vaccination and lose $17 billion with vaccination. In addition, under any demand shift, producers' surplus is declining with or without vaccination. Among all demand shocks, loss of producers' surplus is the largest under demand shift in both domestic and international market with -$20 billion without vaccination and -$36 billion with vaccination.

Table 5-9 Changes in Total Producers' Surplus (in billion 2004 dollars)

	No vaccination	Vaccination
Base	36.35	36.35
No demand	1.38	-17.04
5% domestic demand	-18.09	-34.17
5% excess demand	-1.42	-19.85
5% domestic and excess	-20.10	-36.06

Figures 5-7 and 5-8 show changes in producers' surplus under demand shocks. In two cases, vaccination strategy dominates no vaccination strategy with a higher cost. However, the difference between no vaccination and vaccination becomes smaller when demand shifts in both domestic and international markets by 5%.

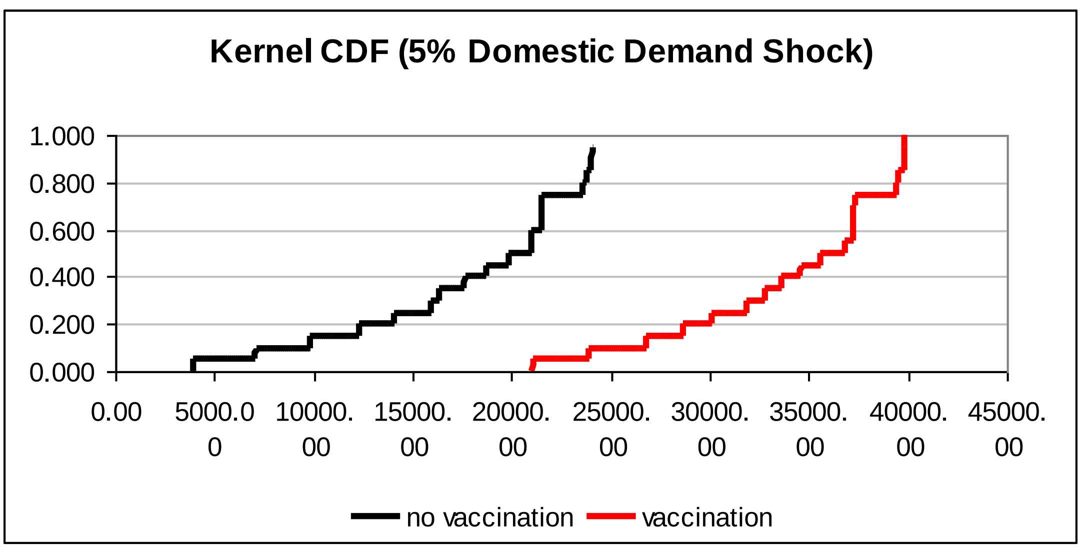


Figure 5-7 Producers' Welfare Losses under 5% Domestic Demand Shock

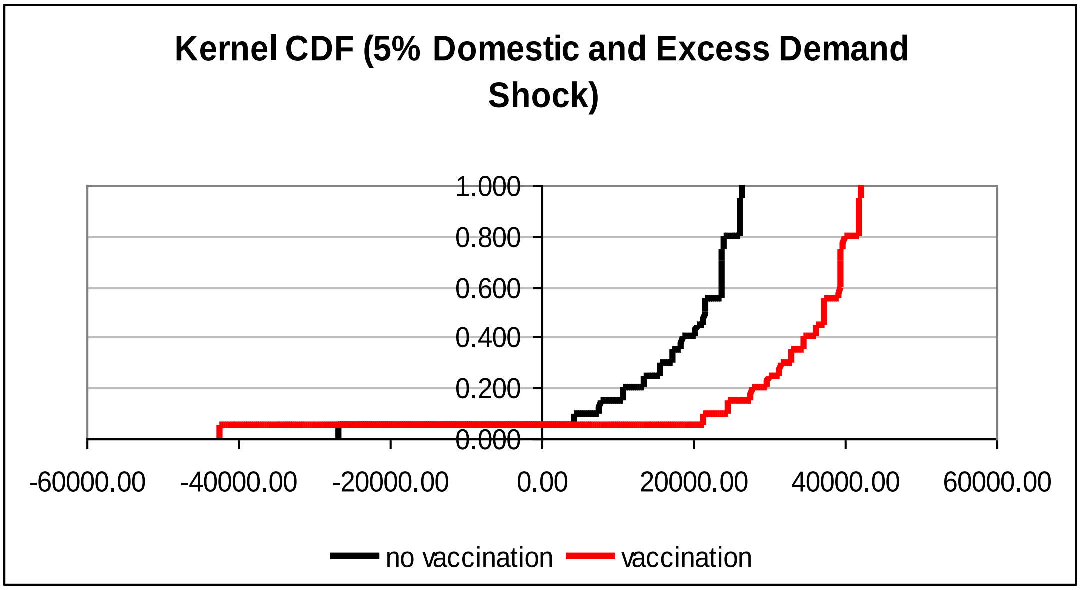
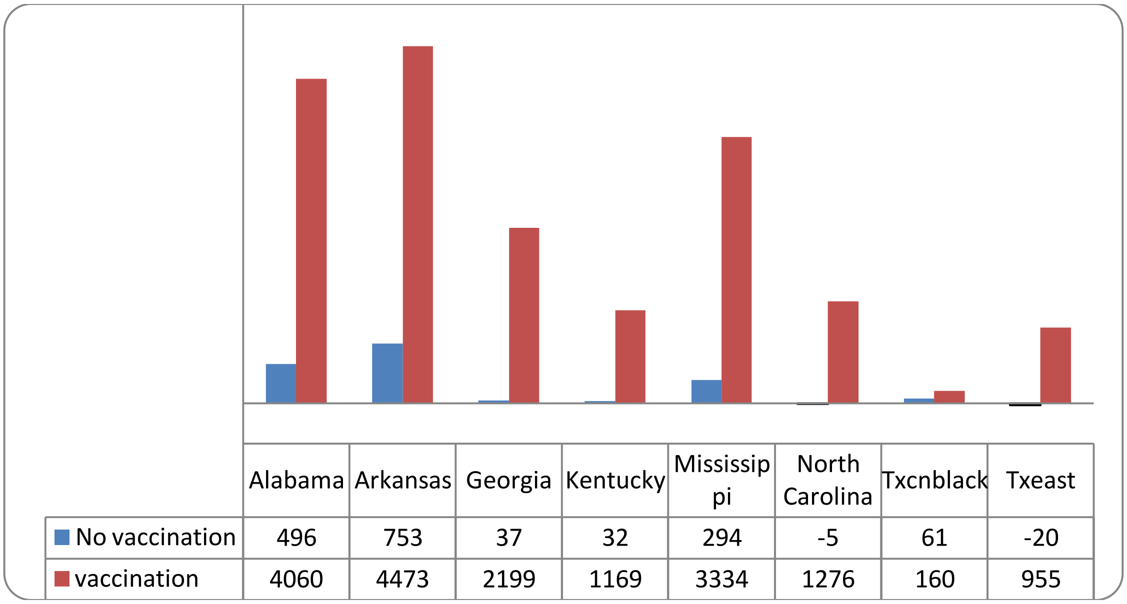


Figure 5-8 Producers' Welfare Losses under Both 5% Demand Shock

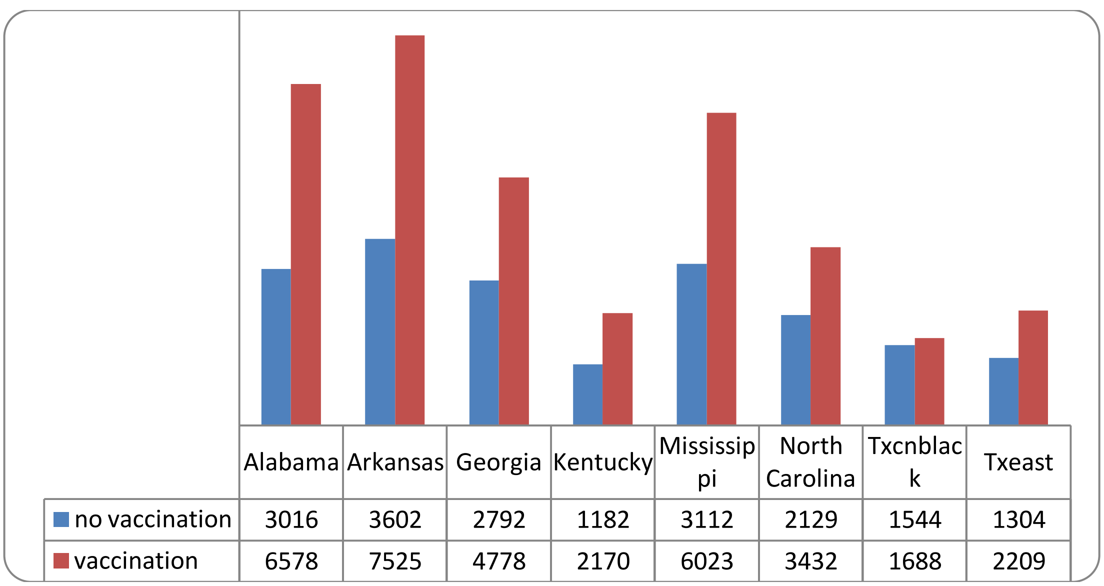
5.4.2.2 Regional total mitigation costs

If there is a AI outbreak in the United States, the welfare of Alabama, Arkansas, Georgia, Kentucky, Mississippi, North Carolina, Texas Central Black lands and Texas East is damaged due to changes in consumers' or producers' surplus. The magnitudes of mitigation cost are determined by how serious the demand shifts in both domestic and international markets as well as by whether vaccination strategy is used.



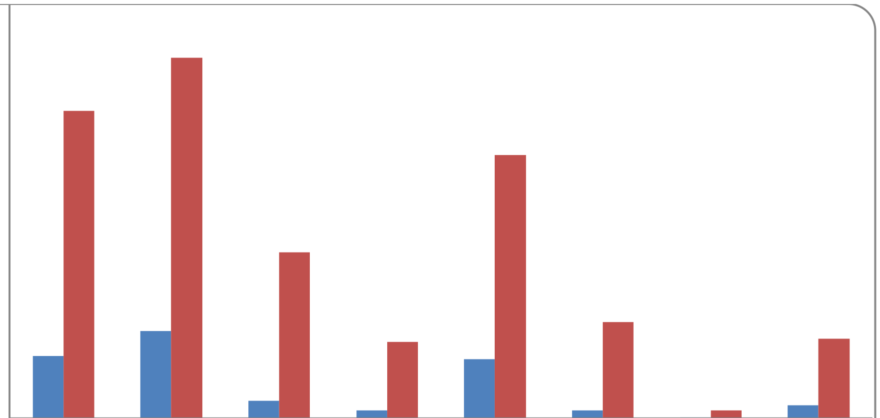
	Alabama	Arkansas	Georgia	Kentucky	Mississip pi	North Carolina	Txcnblack	Txeast
No vaccination	496	753	37	32	294	-5	61	-20
vaccination	4060	4473	2199	1169	3334	1276	160	955

Figure 5-9 Total Costs of AI Outbreaks with No Demand Shock



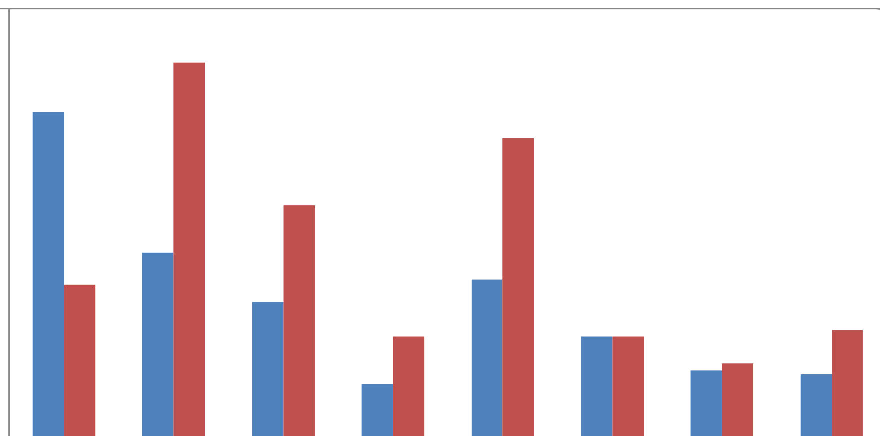
	Alabama	Arkansas	Georgia	Kentucky	Mississip pi	North Carolina	Txcnblac k	Txeast
no vaccination	3016	3602	2792	1182	3112	2129	1544	1304
vaccination	6578	7525	4778	2170	6023	3432	1688	2209

Figure 5-10 Total Costs of AI Outbreaks with 5% Domestic Demand Shift



	Alabama	Arkansas	Georgia	Kentucky	Mississippi	North Carolina	Txcnblack	Txeast
no vaccination	906	1269	253	116	855	116	19	191
vaccination	4458	5218	2408	1112	3817	1396	116	1157

Figure 5-11 Total Costs of AI Outbreaks with 5% Excess Demand Shift



	Alabama	Arkansas	Georgia	Kentucky	Mississippi	North Carolina	Txcnblack	Txeast
no vaccination	6863	3955	2943	1244	3404	2223	1521	1448
vaccination	3289	7877	4929	2230	6316	2223	1668	2352

Figure 5-12 Total Costs of AI Outbreaks with Both Demand Shift by 5%

As shown in Figures 5-9 and 5-11, in the case of no demand shock and 5% excess demand shock, total costs of an AI outbreak are smaller if vaccination is not used. With 5% domestic demand shock as in Figure 5-10, damages of an AI outbreak become much more significant across regions and costs without vaccination are still larger than that with vaccination.

Figure 5-12 shows that with 5% domestic and excess demand shock, total costs of an AI outbreak with vaccination are smaller or equal to the case without vaccination in Alabama and North Carolina, and the difference of AI impacts in other regions are smaller under this circumstance than that with other demand shocks.

5.4.3 Changes of National Price and Production

These changes in the price from the no disease base are a key benefit to use the ASM model. They include not just the commodities impacted directly like chicken, turkey and egg but also the price changes in complement and substitute products. This more fully captures the dynamics of who gains and who loses from the disease outbreak (Hagerman 2009).

Assuming there is no domestic and international demand shift, only domestic supply is affected and it shifts to left due to depopulation of latent and infected flocks and remove of dead flocks. As shown in Figure 5-1, supply shock causes a higher national price and probably less production. However, magnitudes of price and production changes depend on whether farmers have implemented vaccination strategy or not. If vaccination is implemented, fewer birds will be infected, so supply will shift less compared to the condition if vaccination is not used.

Changes of national price and production from the base can be found in Table 5-10. Specifically, in the base scenario, the national price of eggs, live broiler and live turkey is about $0.892/dozen, $0.508/lb, and $0.455/lb, respectively. Without vaccination, price goes up to $1.5/dozen for egg, $0.517/lb for live broiler and $0.463/lb for live turkey. If vaccination strategy is used, price increases less with $1.02/dozen for egg, $0.512/lb for live broiler and turkey price is unchanged.

National prices are declining and results are very sensitive to demand shocks, so I report mean prices with 95% confidence interval in Table 5-10. Among all three types of demand shifts, prices of chicken and turkey are the highest when only international market is affected by the AI outbreak. However, they become the worst if domestic and excess demand shifts together. With the same demand shifts, changes in prices are larger when vaccination strategy is used.

Table 5-10 National Price with Domestic and Excess Demand Shifts ($/ unit)

		No vaccination			Vaccination		
	Base	Mean	95% C.I. [Lower, Upper]		Mean	95% C.I. [Lower, Upper]	
			5% domestic demand shift				
Eggs	0.892	0.1785	0.0000	0.9359	0.1379	0.0000	0.8866
Chicken	69.209	37.4423	20.1920	69.0896	37.2132	20.1920	69.0896
Turkey	68.302	35.1221	15.0460	68.1874	34.7479	15.0460	68.1754
			5% excess demand shift				
Eggs	0.892	1.4682	0.9071	1.4970	1.0206	0.8954	1.0270
Chicken	69.209	61.1541	54.6635	69.1982	60.8608	54.6360	69.1982
Turkey	68.302	65.2890	62.1100	69.3394	64.6567	62.1100	68.2962
			5% domestic demand and 5% excess demand shift				
Eggs	0.892	0.1785	0.0000	0.9359	0.1379	0.0000	0.8866
Chicken	69.209	31.3099	11.5810	69.0556	31.1420	11.5810	69.0556
Turkey	68.302	31.8049	7.9564	68.1754	31.5755	7.9564	68.1472

Table 5-11 shows that production of eggs, broilers and turkeys are most affected by intervention options rather than by demand shifts since changes in national production are the same under different demand shocks.

Table 5-11 National Production under Different Demand Shifts (million units)

	Base	5% domestic demand shift	5% excess demand shift	5% domestic & 5% excess demand shifts	Percent changes (%)
			No vaccination		
Eggs	6693.0389	6344.667	6344.667	6344.667	-5.20
Broilers	342.6115	341.0146	341.0146	341.0146	-0.47
Turkeys	62.3054	61.9378	61.9378	61.9378	-0.59
			Vaccination		
Eggs	6693.0389	6612.431	6612.431	6612.431	-1.20
Broilers	342.6115	342.3165	342.3165	342.3165	-0.09
Turkeys	62.3054	62.2885	62.2885	62.2885	-0.03

5.5 Costs of Past Climate Change

Results in previous section are based on the assumption that there is an AI outbreak in the United States. However, according to findings in Section 3, the probability of AI outbreaks will be 0.116 and 0.077 corresponding to current and past climate conditions, which suggests that the probability of an AI outbreak have been almost doubled increasing by 50% from a base of 0.077 due to past climate change. Therefore, it would be interesting to see how much costs of an AI outbreak are caused by past climate change. I use this probability to do an ex post analysis and Table 5-12 gives the total mitigation costs caused by past climate change in each affected region.

Generally, without any demand shock and vaccination, Texas East gains from the AI outbreaks for about \$0.12 million, while Arkansas has the largest costs up to \$4.67 million. With vaccination, Texas Central Black land has the lowest mitigation costs of \$0.99 million and again Arkansas has the highest cost of \$27.73 million.

Table 5-12 Mitigation Costs of the AI Outbreak Due to Past Climate Change

Regions	AL	AR	GE	KY	AL	AR	GE	KY
	Without vaccination				With vaccination			
				No demand shock				
CS	-0.44	-0.26	-0.69	-0.40	-0.12	-0.07	-0.19	-0.11
PS	-2.63	-4.41	0.47	0.20	-25.05	-27.66	-13.45	-7.14
Total costs	3.08	4.67	0.23	0.20	25.17	27.73	13.63	7.25
				5% domestic demand shock				
CS	-4.27	-2.49	-6.71	-3.85	-4.23	-2.46	-6.64	-3.81
PS	-14.43	-19.85	-10.60	-3.48	-36.56	-44.19	-22.98	-9.65
Total costs	18.70	22.33	17.31	7.33	40.78	46.66	29.62	13.45
				5% excess demand shock				
CS	-0.19	-0.11	-0.30	-0.17	0.14	0.08	0.22	0.12
PS	-5.43	-7.76	-1.27	-0.55	-27.78	-32.43	-15.15	-7.01
Total costs	5.62	7.87	1.57	0.72	27.64	32.35	14.93	6.89
				5% domestic and excess demand shock				
CS	-4.12	-2.39	-6.47	-3.71	-4.09	-2.37	-6.42	-3.68
PS	-38.43	-22.13	-11.78	-4.00	-16.31	-46.46	-24.14	-10.14
Total costs	42.55	24.52	18.25	7.71	20.39	48.84	30.56	13.83

Table 5-12 Continued

Regions	MS	NC	CTBK	EAST	MS	NC	CTBK	EAST
	Without vaccination				With vaccination			
				No demand shock				
CS	-0.29	-0.71	-0.77	-0.18	-0.07	-0.19	-0.20	-0.05
PS	-1.54	0.74	0.39	0.30	-20.60	-7.73	-0.79	-5.87
Total costs	1.82	-0.03	0.38	-0.12	20.67	7.91	0.99	5.92
				5% domestic demand shock				
CS	-4.92	-6.80	-7.41	-1.75	-4.92	-6.72	-7.33	-1.73
PS	-14.37	-6.41	-2.16	-6.34	-32.43	-14.56	-3.13	-11.97
Total costs	19.29	13.20	9.57	8.08	37.34	21.28	10.47	13.70
				5% excess demand shock				
CS	-0.26	-0.30	-0.33	-0.08	-0.06	0.22	0.24	0.06
PS	-5.04	-0.42	0.21	-1.11	-23.60	-8.87	-0.96	-7.23
Total costs	5.30	0.72	0.12	1.18	23.67	8.66	0.72	7.17
				5% domestic and excess demand shock				
CS	-4.80	-6.55	-7.15	-1.69	-4.80	-6.55	-7.09	-1.67
PS	-16.31	-7.23	-2.28	-7.29	-34.35	-7.23	-3.26	-12.91
Total costs	21.10	13.78	9.43	8.98	39.16	13.78	10.34	14.58

Note: CS indicates consumers' surplus and PS indicates producers' surplus.

With 5% demand shock and no vaccination, the mitigation costs would range from \$8.08 to \$22.33 million. With vaccination, costs fall in the range of \$10.47 to \$46.66 million.

With 5% excess demand shock and no vaccination, the mitigation costs would range from \$0.12 to \$7.87 million. With vaccination, costs would fill in the range of \$0.72 to \$32.35 million.

With both excess demand and domestic demand shift by 5% and no vaccination, the mitigation costs would range from \$7.71 to \$42.55 million. With vaccination, costs would fill in the range of \$10.34 to \$ 48.84million.

5.6 Concluding Remarks

This paper uses an epidemic model and an agricultural sector model to examine the cost-effectiveness of mitigation strategies in the face of a simulated U.S. AI outbreak. In addition, results from Section 3 are used to calculate the expected AI mitigation costs due to past climate change under alternative intervention options and different demand shocks.

Results show that vaccination strategy is not generally favorable unless there is both domestic and international demand growth. This result is inconsistent to Egbendewe (2009) where he carried out a regional study of three districts in Texas and assumed that price is exogenous. Results in this paper are consistent with the theoretical analysis that benefits coming from vaccination may be offset by a higher national price caused by no vaccination.

6. SUMMARY AND CONCLUSIONS

This dissertation investigates economic issues regarding AI disease by examining three aspects of the issue as follows,

- The effects of climate on the probability and outcomes of HPAI outbreaks plus the associated economic impacts of climate change of the last 20 years and that projected for the next 20 years
- The effects of AI outbreak media information on meat demand for beef, pork, chicken and turkey in the United States
- The effects of AI mitigation strategies on poultry production and welfare in the United States

This section provides an executive summary of the main procedures/results and identifies directions for future research.

6.1 Summary and Conclusion

Essay 1 in Section 3 examines the relationship between climate conditions and the spread of HPAI outbreaks. I evaluate the outbreak probability and expected numbers as well as associated economic loss under past and future climate change by using econometric methods. Specifically, I estimate outbreak probability over panel data and use count regression models to investigate underreporting issue and the effects of climate conditions on the expected numbers of HPAI outbreaks. Finally, I project the probability of and expected loss to HPAI outbreaks under past and future climate change.

Resutls from estimation models are expected. Particularly, the risk and the expected numbers of HPAI outbreaks are found to increase in areas with higher temperatures in spring and heavier precipitation in winter. Past climate change plays a significant role in increasing the proabbility of disease outbreaks by 11% and that this probability will increase under future climate change by another 12%. Furthermore, I find the issue of underreporting HPAI cases is more serious in countries with lower GDP, larger export of poultry products and more cases of confirmed HPAI human death cases. Consequently, the associated economic loss due to HPAI outbreaks under climate change is larger for countries located in lower latitudes with higher temperature in spring and heavier precipitation in winter. Therefore, disease prevention and control plans should focus on these economically poor and environmentally changed regions.

Essay 2 in Section 4 investigates how media coverage of AI outbreaks affects meat demand in the United States. It contains an econometric analysis using monthly meat demand data from January 1989 to December 2010.

The results show that AI outbreaks information has significant effects on meat demand in the United States. In particular, impacts of overseas AI human deaths on meat expenditure are very small but statistically significant, equaling 0.02% for beef, -0.005% for pork, and -0.01% for chicken for period when there was no AI occurred in the United States, while it has smaller impacts on meat expenditure if using the whole sample. In addition, human death due to AI disease will increase beef expenditure and decrease that for pork and chicken. However, AI media coverage in short-run has insignificant effects on meat demand in United States. From a long run point of view, results show that consumers are more cautious when animal disease cases occur within the United States as opposed to international cases.

Essay 3 in Section 5 focuses on the comparison between two AI control strategies, vaccination and no vaccination extending Egbendewe (2009)'s study to a national basis. An epidemiologic susceptible-latent-infected-recovered (SLIR) model and an Agricultural Sector model (ASM) are used together to examine the cost effectiveness of these two strategies and associated costs due to past climate change are also calculated.

Results find that vaccination strategy is not favorable under most cases with different demand shocks unless demand decreases across the board. Under the assumption of one AI outbreak in the United States, the associated mitigation costs because of past climate change are relatively small. For example in Texas, about $2 million in additional costs are estimated under past climate change.

6.2 Limitation and Future Research

There are several limitations of studies in this dissertation and these limitations could be addressed and developed in future research.

In essay 1, I use a set of dummy variables to reflect whether a country is on wild bird migratory flyways, which does not differentiate among flyways and whether or not prior and recent outbreaks have occurred on this flyway. Future study needs to refine this by constructing a more specific and complex flyway indices.

In essay 2, I use the dynamic inverse almost ideal demand system model (IAIDS) to estimate effects of AI media coverage on meat demand; however, this model is used based solely on time series properties. The theoretical limitation of the dynamic IAIDS model could be further examined and alternative models could be compared and tested in future studies.

In essay 3, the assumption of the constant contact rate among all regions does not take account of differential geographic characteristics across regions, and this should be investigated further. In addition, as stated by Egbendewe (2009), it would be interesting to introduce a contact rate with live birds.

REFERENCES

Adams, D., R. Alig, B.A. McCarl, B.C. Murray, L. Bair, B. Depro, G. Latta, H.C. Lee, U.A. Schneider, and J.M. Callaway. 2005. "FASOMGHG Conceptual Structure, and Specification: Documentation." Unpublished, Department of Agricultural Economics, Texas A&M University, College Station.

Ai, C., and E.C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters* 80(1):123-129.

Akey, B.L. 2003. "Low-pathogenicity H7N2 Avian Influenza Outbreak in Virginia during 2002." *Avian Diseases* 47(s3):1099-1103.

Alexander, D.J. 2007. "An Overview of the Epidemiology of Avian Influenza." *Vaccine* 25(30):5637-5644.

---. 2000. "A Review of Avian Influenza in Different Bird Species." *Veterinary Microbiology* 74(1-2):3-13.

Aznar, A., and M. Salvador. 2002. "Selecting the Rank of the Cointegration Space and the Form of the Intercept Using an Information Criterion." *Econometric Theory* 18(4):926-947.

Baldwin, M.A., and M. Hadid, and G.D.A. Phillips. 1983. "The Estimation and Testing of a System of Demand Equations for the UK." *Applied Economics* 15(1):81-90.

Baltagi, B.H., and Z. Wang. 2007. "Testing for Cointegrating Rank via Model Selection: Evidence from 165 Data Sets." *Empirical Economics* 33(1):41-49.

Basuno, E., and Y. Yusdja, and N. Ilham. 2010. "Socio-economic Impacts of Avian Influenza Outbreaks on Small-scale Producers in Indonesia." *Transboundary and Emerging Diseases* 57(1-2):7-10.

Beach, R.H., and C. Zhen. 2008. "Consumer Purchasing Behavior in Response to Media Coverage of Avian Influenza. " Paper presented at SAEA annual meeting, Dallas TX, 2-5 February.

Bilgic, A., and W.J. Florkowski. 2007. "Application of A Hurdle Negative Binomial Count Data Model to Demand for Bass Fishing in the Southeastern United States." *Journal of Environmental Management* 83(4):478-490.

Brahmbhatt, M. 2005. *Avian Influenza: Economic and Social Impacts*. Washington DC: the World Bank, September 23. Available from: http://go.worldbank.org/P6GU56G250.

Brier, G.W. 1950. "Verification of Forecasts Expressed in Terms of Probability." *Monthly Weather Review* 78(1):1-3.

Brown, J.D., D.E. Swayne, R.J. Cooper, R.E. Burns, and D.E. Stallknecht. 2007. "Persistence of H5 and H7 Avian Influenza Viruses in Water." *Avian Diseases* 51(s1):285-289.

Burns, A., and D. van der Mensbrugghe, and H. Timmer. 2008. *Evaluating the Economic Consequences of Avian Influenza*. Washington DC: the World Bank. Available from: http://siteresources.worldbank.org/EXTAVIANFLU/Resources/EvaluatingAHIeconomics_2008.pdf.

Burton, M., and T. Young. 1996. "The Impact of BSE on the Demand for Beef and Other Meats in Great Britain." *Applied Economics* 28(6):687-693.

Cameron, A.C., and P.K. Trivedi. 2009. *Microeconometrics Using Stata*. College Station TX: Stata Press.

---. 1998. *Regression Analysis of Count Data*. Cambridge U.K. and New York U.S.: Cambridge University Press.

CASERED (Indonesian Centre of Agricultural Socio-Economic Research and Development). 2004. *Socio-economic Impact Assessment of the Avian Influenza Crisis in Poultry Production System in Indonesia, with Particular Focus on Independent Smallholders*. Final Report for FAO' TCP/RAS/3010 "Emergency Regional Support for Post Avian Influenza Rehabilitation". Rome Italy: Food and Agriculture Organization.

Casillas-Olvera, G., and D.A. Bessler. 2006. "Probability Forecasting and Central Bank Accountability." *Journal of Policy Modeling* 28(2):223-234.

CDC. 2010. *Information on Avian Influenza*. Available from: http://www.cdc.gov/flu/avianflu/.

Chamberlain, G. 1980. "Analysis of Covariance with Qualitative Data." *Review of Economic Studies* 47(1):225-238.

Chan, P.K.S. 2002. "Outbreak of Avian Influenza A (H5N1) Virus Infection in Hong Kong in 1997." *Clinical Infectious Diseases* 34(S2):58-64.

Chen, H., G.J.D. Smith, S.Y. Zhang, K. Qin, J. Wang, K.S. Li, R.G. Webster, J.S.M. Peiris, and Y. Guan. 2005. "H5N1 Virus Outbreak in Migratory Waterfowl." *Nature* 436(14):191–192.

Chong, Y.Y., and D.F. Hendry. 1986. "Econometric Evaluation of Linear Macro-economic Models." *Review of Economic Studies* 53(4):671-690.

Clemente, J., and A. Montañes, and M. Reyes. 1998. "Testing for a Unit Root in Variables with a Double Change in the Mean." *Economics Letters* 59(2):175-182.

Collins, M., and S.F.B. Tett, and C. Cooper. 2001. "The Internal Climate Variability of HadCM3, a Version of the Hadley Centre Coupled Model without Flux Adjustments." *Climate Dynamics* 17(1):61-81.

Cooper, R.G., and C. Tomasik, and J.O. Horbanczuk. 2007. "Avian Influenza in Ostriches (Struthio Camelus)." *Avian and Poultry Biology Reviews* 18(3):87-92.

Cui, P., Y. Hou, Z. Xing, Y. He, T. Li, S. Guo, Z. Luo, B. Yan, Z. Yin, and F. Lei. 2011. "Bird Migration and Risk for H5N1 Transmission into Qinghai Lake, China." *Vector-Borne and Zoonotic Diseases* 11(5):567-576.

Cupp, O.S., and D.E. Walker, and J. Hillison. 2004. "Agroterrorism in the U.S.: Key Security Challenge for the 21st Century." *Biosecurity and Bioterrorism: Biodefense Strategy, Practice, and Science* 2(2):97-105.

Deaton, A., and J. Muellbauer. 1980. "An Almost Ideal Demand System." *The American Economic Review* 70(3):312-326.

Deaton, A.S. 1974. "The Analysis of Consumer Demand in the United Kingdom, 1900-1970." *Econometrica* 42:341-367.

---. 1972. "The Estimation and Testing of Systems of Dmeand Equations: A note." *European Economic Review* 3(4):399-411.

Delquigny, T., M. Edan, D.H. Nguyen, T.K. Pham, and P. Gautier. 2004. *Evolution and Impact of Avian Influenza Epidemic and Description of the Avian Production in Vietnam.* Final Report for FAO’s TCP/RAS/3010 "Emergency Regional Support for Post Avian Influenza Rehabilitation". Rome Italy: Food and Agriculture Organization.

Delworth, T.L., A.J. Broccoli, A. Rosati, R.J. Stouffer, V. Balaji, J.A. Beesley, W.F. Cooke, K.W. Dixon, J. Dunne, and K.A. Dunne. 2006. "GFDL's CM2 Global Coupled Climate Models. Part I: Formulation and Simulation Characteristics." *Journal of Climate* 19(5):643-674.

Donnelly, C.A., M.C. Fisher, C. Fraser, A.C. Ghani, S. Riley, N.M. Ferguson, and R.M. Anderson. 2004. "Epidemiological and Genetic Analysis of Severe Acute Respiratory Syndrome." *The Lancet Infectious Diseases* 4(11):672-683.

Duffy, M. 2003. "Advertising and Food, Drink and Tobacco Consumption in the United Kingdom: A Dynamic Demand System." *Agricultural Economics* 28(1):51-70.

---. 2006. "Tobacco Consumption and Policy in the United Kingdom." *Applied Economics* 38(11):1235-1257.

Eales, J.S., and L.J. Unnevehr. 1994. "The Inverse Almost Ideal Demand System." *European Economic Review* 38(1):101-115.

Easkins, J.M., and L.A. Gallagher. 2003. "Dynamic Almost Ideal Demand Systems: An Empirical Analysis of Alcohol Expenditure in Ireland." *Applied Economics* 35(9):1025-1036.

Egbendewe-Mondzozo, A. 2009. "Integrated Economic-epidemic Modeling of Avian Influenza Mitigation Options: A Case Study of An Outbreak in Texas." Ph.D. dissertation, Texas A&M University, College Station.

Elbakidze, L. 2008. "Modeling of Avian Influenza Mitigation Policies within the Backyard Segment of the Poultry Sector." *Journal of Agricultural and Resource Economics* 33(2):195-211.

Elder, J. 1997. "Estimating the Arbitrage Pricing Theory with Observed Macro Factors." *Economics Letters* 55(2):241-246.

Engle, R.F., and C.W.J. Granger. 1987. "Co-integration and Error Correction: Representation, Estimation, and Testing." *Econometrica* 55:251-276.

European Food Safety Authority. 2005. "Migratory Birds and Their Possible Role in the Spread of Highly Pathogenic Avian Influenza." *The EFSA Journal* 357:1-46.

Fang, L.Q., S.J. De Vlas, S. Liang, C.W.N. Looman, P. Gong, B. Xu, L. Yan, H. Yang, J.H. Richardus, and W.C. Cao. 2008. "Environmental Factors Contributing to the Spread of H5N1 Avian Influenza in Mainland China." *PLoS One* 3(5):e2268. Doi:10.1371/journal.pone.0002268.

Feare, C.J. 2007. "The Role of Wild Birds in the Spread of HPAI H5N1." *Avian Diseases* 51(1):440-447.

Gilbert, M., X. Xiao, J. Domenech, J. Lubroth, V. Martin, and J. Slingenbergh. 2006. "Anatidae Migration in the Western Palearctic and Spread of Highly Pathogenic Avian Influenza H5N1 Virus." *Emerging Infectious Diseases* 12(11):1650-1656.

Gilbert, M., X. Xiao, D.U. Pfeiffer, M. Epprecht, S. Boles, C. Czarnecki, P. Chaitaweesub, W. Kalpravidh, P.Q. Minh, and M.J. Otte. 2008. "Mapping H5N1 Highly Pathogenic Avian Influenza Risk in Southeast Asia." *Proceedings of the National Academy of Sciences* 105(12):4769-4774.

Gnanadesikan, A., K.W. Dixon, S.M. Griffies, V. Balaji, M. Barreiro, J.A. Beesley, W.F. Cooke, T.L. Delworth, R. Gerdes, and M.J. Harrison. 2006. "GFDL's CM2 Global Coupled Climate Models. Part II: The Baseline Ocean Simulation." *Journal of Climate* 19(5):675-697.

Green, R., and J.M. Alston. 1990. "Elasticities in AIDS Models." *American Journal of Agricultural Economics* 72(2):442-445.

---. 1991. "Elasticities in AIDS Models: A Clarification and Extension." *American Journal of Agricultural Economics* 73(3):874-875.

Groisman, P.Y., R.W. Knight, D.R. Easterling, T.R. Karl, G.C. Hegerl, and V.N. Razuvaev. 2005. "Trends in Intense Precipitation in the Climate Record." *Journal of Climate* 18(9):1326-1350.

Hagerman, A.M. 2009. "Essays on Modeling the Economics Impacts of Foreign Animal Disease on the U.S. Agricultural Sector." Ph.D. dissertation, Texas A&M University, College Station.

Hahn, W.F. 1994. "Elasticities in AIDS Models: Comment." *American Journal of Agricultural Economics* 76(4):972-977.

Hogerwerf, L., R.G. Wallace, D. Ottaviani, J. Slingenbergh, D. Prosser, L. Bergmann, and M. Gilbert. 2010. "Persistence of Highly Pathogenic Avian Influenza H5N1 Virus Defined by Agro-ecological Niche." *EcoHealth* :1-13.

Hu, M.C., and M. Pavlicova, and E.V. Nunes. 2011. "Zero-inflated and Hurdle Models of Count Data with Extra Zeros: Examples from An HIV-risk Reduction Intervention Trial." *The American Journal of Drug and Alcohol Abuse* 37(5):367-375.

Ishida, T., and N. Ishikawa, and M. Fukushige. 2010. "Impact of BSE and Bird Flu on Consumers’ Meat Demand in Japan." *Applied Economics* 42(1):49-56.

Jin, Y., and J. Mu. 2012. "Avian Influenza in China: Consumer Perception of AI and Their Willingness to Pay for Traceability Labeling." *Health and Animal Agriculture in Developing Countries* :391-399.

Johansen, S. 1988. "Statistical Analysis of Cointegration Vectors." *Journal of Economic Dynamics and Control* 12(2-3):231-254.

Kastens, T.L., and G.W. Brester. 1996. "Model Selection and Forecasting Ability of Theory-constrained Food Demand Systems." *American Journal of Agricultural Economics* 78(2):301-312.

Kilpatrick, A.M., A.A. Chmura, D.W. Gibbons, R.C. Fleischer, P.P. Marra, and P. Daszak. 2006. "Predicting the Global Spread of H5N1 Avian Influenza." *Proceedings of the National Academy of Sciences* 103(51):19368-19373.

Klaiber, H.A., and M.T. Holt. 2010. "The Role of Theoretical Restrictions in Forecasting with Inverse Demand Models." *American Journal of Agricultural Economics* 92(1):70-85.

Kunkel, K.E. 2003. "North American Trends in Extreme Precipitation." *Natural Hazards* 29(2):291-305.

Li, F.C.K., B.C.K. Choi, T. Sly, and A.W.P. Pak. 2008. "Finding the Real Case-fatality Rate of H5N1 Avian Influenza." *Journal of Epidemiology and Community Health* 62:555-559. Doi:10.1136/jech.2007.064030.

Liu, C.M., S.H. Lin, Y.C. Chen, K.C. Lin, T.S. Wu, and C.C. King. 2007. "Temperature Drops and the Onset of Severe Avian Influenza A H5N1 Virus Outbreaks." *PLoS One* 2(2):e191. Doi:10.1371/journal.pone.0000191.

Lloyd-Smith, J.O. 2007. "Maximum Likelihood Estimation of the Negative Binomial Dispersion Parameter for Highly Overdispersed Data, with Applications to Infectious Diseases." *PLoS One* 2(2):e180. Doi:10.1371/journal.pone.0000180.

Marsh, T.L., and T.C. Schroeder, and J. Mintert. 2004. "Impacts of Meat Product Recalls on Consumer Demand in the U.S.A." *Applied Economics* 36(9):897-909.

Mazzocchi, M. 2006. "No News Is Good News: Stochastic Parameters versus Media Coverage Indices in Demand Models after Food Scares." *American Journal of Agricultural Economics* 88(3):727-741.

---. 2003. "Time-varying Coefficients in the Almost Ideal Demand System: An Empirical Appraisal." *European Review of Agricultural Economics* 30(2):241-270.

McElroy, M.B., and E. Burmeister. 1988. "Arbitrage Pricing Theory as a Restricted Nonlinear Multivariate Regression Model: Iterated Nonlinear Seemingly Unrelated Regression Estimates." *Journal of Business & Economic Statistics* 6(1):29-42.

McLeod, A., N. Morgan, A. Prakash, and J. Hinrichs. 2005. *Economic and Social Impacts of Avian Influenza*. Rome Italy: Food and Agriculture Organization of the United Nations, Emergency Centre for Transboundary Animal Diseases Operations (ECTAD).

Meisner, J.F. 1979. "The Sad Fate of the Asymptotic Slutsky Symmetry Test for Large Systems." *Economics Letters* 2(3):231-233.

Morana, C. 2000. "Modelling Evolving Long-run Relationships: An Application to the Italian Energy Market." *Scottish Journal of Political Economy* 47(1):72-93.

Nakićenović, N. 2000. *IPCC Special Report on Emissions Scenarios (SRES*). Cambridge U.K. and New York U.S.: Cambridge University Press.

Nature editorial. 2006."Dreams of Flu Data." *Nature*, no. 440, pp: 255–256.

Newman, S.H., J. Siembieda, R. Kock, T. McCracken, S. Khomenko, T. Mundkur. 2010. *FAO EMPRES Wildlife Unit Fact Sheet: Wildlife and H5N1 HPAI Virus-Current Knowledge.* Rome Italy: Food and Agriculture Organization of the United Nations, Animal Production and Health Division.

Nicita, A. 2008. *Avian Influenza and the Poultry Trade*. Washington DC: The World Bank, Development Research Group.

Nordqvist, Christian. 2006. "Total Bird Flu Cases Under-reported In China, Indonesia and Africa." *Medical News Today.* Available from: http://www.medicalnewstoday.com/articles/44318.php.

Norton, E.C., and H. Wang, and C. Ai. 2004. "Computing Interaction Effects and Standard Errors in Logit and Probit Models." *Stata Journal* 4(2):154-167.

Ottaviani, D., S. De La Rocque, S. Khomenko, M. Gilbert, S.H. Newman, B. Roche, K. Schwabenbauer, J. Pinto, T.P. Robinson, and J. Slingenbergh. 2010. "The Cold European Winter of 2005–2006 Assisted the Spread and Persistence of H5N1 Influenza Virus in Wild Birds." *EcoHealth* :1-11.

Otte, J., J. Hinrichs, J. Rushton, D. Roland-Holst, and D. Zilberman. 2008. "Impacts of Avian Influenza Virus on Animal Production in Developing Countries." *CAB*

Reviews: Perspectives on Agriculture, Veterinary Science, Nutrition and Natural Resources 3(080): unpaged.

Paarlberg, P.L., and J.G. Lee, and A.H. Seitzinger. 2005. "Economic Modeling of Livestock Disease Outbreaks." *International Food and Agribusiness Management Review* 8(1):62-67.

Page, S., I. Yeoman, C. Munro, J. Connell, and L. Walker. 2006. "A Case Study of Best Practice--Visit Scotland's Prepared Response to an Influenza Pandemic." *Tourism Management* 27(3):361-393.

Park, M., and Y.H. Jin, and D.A. Bessler. 2008. "The Impacts of Animal Disease Crises on the Korean Meat Market." *Agricultural Economics* 39(2):183-195.

Paul, M., S. Tavornpanich, D. Abrial, P. Gasqui, M. Charras-Garrido, W. Thanapongtharm, X. Xiao, M. Gilbert, F. Roger, and C. Ducrot. 2010. "Anthropogenic Factors and the Risk of Highly Pathogenic Avian Influenza H5N1: Prospects from a Spatial-based Model." *Veterinary Research* 41(3):28. DOI: 10.1051/vetres/2009076.

Peiris, J.S.M., and M.D. De Jong, and Y. Guan. 2007. "Avian Influenza Virus (H5N1): A Threat to Human Health." *Clinical Microbiology Reviews* 20(2):243-267.

Peiris, J.S.M., W.C. Yu, C.W. Leung, C.Y. Cheung, W.F. Ng, J.M. Nicholls, T.K. Ng, K.H. Chan, S.T. Lai, and W.L. Lim. 2004. "Re-emergence of Fatal Human Influenza A Subtype H5N1 Disease." *The Lancet* 363(9409):617-619.

Pelzel, A.M., and B.J. McCluskey, and A.E. Scott. 2006. "Review of the Highly Pathogenic Avian Influenza Outbreak in Texas, 2004." *Journal of the American Veterinary Medical Association* 228(12):1869-1875.

Pfeiffer, D.U., I. Brown, R.A.M. Fouchier, N. Gaidet, V. Guberti, T. Harder, R. Langston, and R.J. Soares Magalhaes. 2006. "Opinion of the Scientific Panel Animal Health and Welfare (AHAW) Related with the Migratory Birds and Their Possible Role in the Spread of Highly Pathogenic Avian Influenza." *EFSA Journal* 4(5):1-46.

Phillips, P.C.B., and J.W. McFarland. 1997. "Forward Exchange Market Unbiasedness: The Case of the Australian Dollar since 1984." *Journal of International Money and Finance* 16(6):885-907.

Piggott, N.E., and T.L. Marsh. 2004. "Does Food Safety Information Impact U.S. Meat Demand?" *American Journal of Agricultural Economics* 86(1):154-174.

Piggott, N.E., C. Zhen, R.H. Beach, and M.K. Wolhlgenant. 2007. "The Impact of Pork Advertising on U.S. Meat Demand in the Presence of Competing Beef Advertising and Food Safety Events." Paper presented at AAEA annual meeting, Portland OR, 29 July-1 August.

Pritchett, J., and D. Thilmany, and K. Johnson. 2005. "Animal Disease Economic Impacts: A Survey of Literature and Typology of Research Approaches." *International Food and Agribusiness Management Review* 8(1):23-45.

Ridout, M., and C.G.B. Demétrio, and J. Hinde. 1998. "Models for Count Data with Many Zeros." Paper presented at International Biometric Conference, Cape Town, December.

Rushton, J., R. Viscarra, E.G. Bleich, A. McLeod, and V. Nam. 2006. *Impact of Avian Influenza Outbreaks in the Poultry Sectors of Five South East Asian Countries (Cambodia, Indonesia, Lao PDR, Thailand, Viet Nam): Outbreak Costs, Responses and Potential Long-term Control*. Washington DC: The World Bank.

Salas-Mélia, D., F. Chauvin, M. Déqué, H. Douville, J.F. Gueremy, P. Marquet, S. Planton, J.F. Royer, and S. Tyteca. 2005. "Description and Validation of the CNRM-CM3 Global Coupled Model." Submitted to *Climate Dynamics*.

Schlenker, W., and W.M. Hanemann, and A.C. Fisher. 2006. "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions." *Review of Economics and Statistics* 88(1):113-125.

Scott, L.J., and J. Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*, 2rd. ed. College Station TX: Stata Press.

Senne, D.A. 2007. "Avian Influenza in North and South America, 2002-2005." *Avian Diseases* 51(s1):167-173.

Shahid, M.A., M. Abubakar, S. Hameed, and S. Hassan. 2009. "Avian Influenza Virus (H5N1): Effects of Physico-chemical Factors on Its Survival." *Virology Journal* 6:38. Doi:10.1186/1743-422X-6-38.

Si, Y., A.K. Skidmore, T. Wang, W.F. Boer, P. Debba, A.G. Toxopeus, L. Li, and H.H.T. Prins. 2009. "Spatio-temporal Dynamics of Global H5N1 Outbreaks Match Bird Migration Patterns." *Geospatial Health* 4(1):65-78.

Si, Y., T. Wang, A.K. Skidmore, W.F. De Boer, L. Li, and H.H.T. Prins. 2010. "Environmental Factors Influencing the Spread of the Highly Pathogenic Avian Influenza H5N1 Virus in Wild Birds in Europe." *Ecology and Society* 15(3):26. Available from: http://www.ecologyandsociety.org/vol15/iss3/art26/.

Sims, L.D., and I.H. Brown. 2008. "Multicontinental Epidemic of H5N1 HPAI Virus (1996–2007)." In D. E. Swayne, ed. *Avian Influenza*. Oxford U.K.: Blackwell Publishing Ltd., pp.251-286. DOI: 10.1002/9780813818634.ch11.

Sims, L.D., and C. Narrod. 2008. *Understanding Avian Influenza*, ch1-3. Available from: http://www.fao.org/avianflu/documents/key_AI/key_book_preface.htm.

Solomon, S., D. Qin, M. Manning, M. Marquis, K. Averyt, M.M.B. Tignor, H.L. Miller Jr, and Z. Chen. 2007. *Climate change 2007: The Physical Science Basis*. Cambridge U.K. and New York U.S.: Cambridge University Press.

Taha, F.A., and S. United States. Dept. of Agriculture. Economic Research. 2007. *How Highly Pathogenic Avian Influenza (H5N1) Has Affected World Poultry-meat Trade*. Washington DC: U.S. Dept. of Agriculture, Economic Research Service.

Vaudor, L., and N. Lamouroux, and J.-M. Olivier. 2011. "Comparing Distribution Models for Small Samples of Overdispersed Counts of Freshwater Fish." *Acta Oecologica* 37(3):170-178.

Verbeke, W., and R.W. Ward. 2001. "A Fresh Meat Almost Ideal Demand System Incorporating Negative TV Press and Advertising Impact." *Agricultural Economics* 25(2-3):359-374.

VSF. 2004. *Review of the Poultry Production and Assessment of the Socio-economic Impact of the Highly Pathogenic Avian Influenza Epidemic in Cambodia*. Final Report for FAO's TCP/RAS/3010 "Emergency Regional Support for Post Avian Influenza Rehabilitation". Rome Italy: Food and Agriculture Organization.

Vuong, Q.H. 1989. "Likelihood Ratio Tests for Model Selection and Non-nested Hypotheses." *Econometrica* 57(2):307-333.

Wang, Z. 2010. "Directed Graphs, Information Structure and Forecast Combinations: An Empirical Examination of U.S. Unemployment Rates." *Journal of Forecasting* 29(4):353-366.

Wang, Z., and D.A. Bessler. 2003. "Forecast Evaluations in Meat Demand Analysis." *Agribusiness* 19(4):505-523.

---. 2006. "Price and Quantity Endogeneity in Demand Analysis: Evidence from Directed Acyclic Graphs." *Agricultural Economics* 34(1):87-95.

Ward, M.P., D. Maftei, C. Apostu, and A. Suru. 2008. "Environmental and Anthropogenic Risk Factors for Highly Pathogenic Avian Influenza Subtype

H5N1 Outbreaks in Romania, 2005-006." *Veterinary Research Communications* 32(8):627-634.

Ward, M.P., D.N. Maftei, C.L. Apostu, and A.R. Suru. 2009. "Association between Outbreaks of Highly Pathogenic Avian Influenza Subtype H5N1 and Migratory Waterfowl (Family Anatidae) Populations." *Zoonoses and Public Health* 56(1):1-9.

Williams, R.A.J., and F.O. Fasina, and A.T. Peterson. 2008. "Predictable Ecology and Geography of Avian Influenza (H5N1) Transmission in Nigeria and West Africa." *Transactions of the Royal Society of Tropical Medicine and Hygiene* 102(5):471-479.

Williams, R.A.J., and A.T. Peterson. 2009. "Ecology and Geography of Avian Influenza (HPAI H5N1) Transmission in the Middle East and Northeastern Africa." *International Journal of Health Geographics* 8:47. Doi:10.1186/1476-072X-8-47.

Wooldridge, J.M. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge MA: The MIT press.

---. 2000. "A Framework for Estimating Dynamic, Unobserved Effects Panel Data Models with Possible Feedback to Future Explanatory Variables." *Economics Letters* 68(3):245-250.

---. 2005. "Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity." *Journal of Applied Econometrics* 20(1):39-54.

Yates, J.F. 1988. "Analyzing the Accuracy of Probability Judgments for Multiple Events: An Extension of the Covariance Decomposition." *Organizational Behavior and Human Decision Processes* 41(3):281-299.

Yupiana, Y., S.J. de Vlas, N.M. Adnan, and J.H. Richardus. 2010. "Risk Factors of Poultry Outbreaks and Human Cases of H5N1 Avian Influenza Virus Infection in West Java Province, Indonesia." *International Journal of Infectious Diseases* 14(9):e800-e805.

VITA

Jianhong Mu received her college and graduate education from the School of Agricultural Economics and Rural Development at Renmin University of China (2001 – 2007), where she obtained her Bachelor of Science degree in Economics in 2005 and Master of Science degree in Management in 2007.

She entered the Agricultural Economics PhD program at Texas A&M University in September 2007 and received her PhD degree in Agricultural Economics in May 2012. Her research interests include, but not limited to, the economic effects of avian influenza on demand and production, climate change effects, and development of adaptation and mitigation strategies in agriculture.

Mrs. Mu may be reached at Department of Agricultural Economics, Texas A&M University, 2124 TAMU, College Station, TX 77843-2124. Her email address is mujh1024@gmail.com.