CLIMATE CHANGE INFLUENCES ON THE RISK OF AVIAN INFLUENZA OUTBREAKS AND ASSOCIATED ECONOMIC LOSS

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Abstract:

This paper examines the effect that climate has on Avian Influenza outbreak probability. The statistical analysis shows across a broad region the probability of an outbreak declines by 0.22% when the temperature rises 1 Celsius degree and increases by 0.34% when precipitation increases by 1millimeter. These results indicate that the realized climate change of the last 20 years not only has been a factor behind recent HPAI outbreaks, but that climate change is likely to play an even greater role in the future. The statistical results indicate that overall, the risk of an AI outbreak has been increased by 51% under past climate change and 3-4% under future climate change. An economic evaluation shows the increased probability of outbreaks has caused damages of about $107 million in China and $29 million in the United States due to past climate change. In the year of 2011-2030, for countries with a high proportion of chicken production, economic loss could reach $105-$146 million in China and $12-$18 million in the United Sates.

Keywords: Climate change, Avian Influenza outbreaks, GDP loss

Since 2003, epidemics of the most dangerous avian influenza (AI) strain - high pathogenic avian influenza (HPAI) - have occurred with unprecedented frequency across an ever wider part of the globe. This strain was initially observed in East and Southeast Asia and then migrated to Russia, the Middle East, Europe, Africa and South Asia (Sims 2007). Currently, the list of countries where AI outbreaks have occurred is still expanding (CIRAD 2010).

In the last decade, HPAI has caused significant damage across the globe[i]. Determining the factors involved in its spread and producing risk probabilities is important targeting surveillance and control measures plus ultimately in loss reduction (Paul et al. 2010) plus in planning for disease prevention.

Climate change is a possible factor in the widening spread as it may alter conditions that are involved with disease transmission and persistence including wild bird migration patterns. This paper conducts a statistical examination on the extent to which HPAI outbreak risk is being affected by current climatic conditions and realized/projected climate change. In particular, we examine how temperature, precipitation, seasonality and regional characteristics affect outbreak probability using data from the events in Asia, Europe, Africa and North America. Then we use the estimated statistical results to simulate how much the outbreak probability has shifted due to past and projected climate change. Additionally, we evaluate the increase in expected cost of AI outbreaks stimulated by past and projected future climate change.

This paper is organized as follows. Section 2 and 3 reviews background information on HPAI and previous studies; Section 4 presents the statistical models and describes the data; Section 5 interprets estimation results, predicts the risk of HPAI outbreaks under past and future climate change and evaluates associated economic losses and section 6 presents conclusions.

Background Information on AI

AI, commonly called “bird flu”, is a contagious animal disease that infects birds and some mammals (WHO 2005). The strains of AI are divided into two sub-groups based on their contagiousness and symptom severity: high pathogenic avian influenza (HPAI) and low pathogenic avian influenza (LPAI). The LPAI is less contagious and cause no harm to affected species, while the HPAI virus, such as the H5N1 strain, spreads rapidly with a high mortality rate that can infect up to 100% of contact birds within 48 hours plus can spread to humans (OIE 2008).

AI was initially detected in poultry on a farm in Scotland, UK, in 1959 (Fang et al. 2008) and has since been identified in Europe, North America, Australia (Alexander 2000) Southeast and Central Asia (Peiris et al. 2007), Eastern Europe and Africa. As of summer 2010, twelve countries were experiencing an ongoing epidemic of at least one strain of AI (CIRAD 2010).

Outbreaks of the disease often lead to severe economic losses. HPAI outbreaks led to almost 36 billion chickens being culled in China between 2004 and 2009. In Vietnam, indirect losses due to outbreaks represented are estimates at about 45 to 135 million US dollars (Brambhatt 2005; McLeod et al. 2006). In Laos, total loss amounted to 3% of the national flock, with approximately 80% of the culled birds in a single province (Rushton, et al. 2005). As a consequence of these sizable losses, McLeod et al. (2006) estimated that a South-East Asia wide AI pandemic, including spillover effects, could result in a 1.5% GDP growth reduction for countries heavily invested in poultry.

AI and Climate Change Literature Review

In order to estimate how climate change affects the probability of AI outbreaks, an understanding of factors affecting the spread of the disease is needed. The literature suggests that climate change may alter several items involved with AI spread and persistence.

Climate has been found to alter disease survival and disease vector behavior. In particular experimental evidence shows low temperature and high relative humidity conditions increase the persistence and stability of the AI virus (Animal Health Australia 2005; WHO 2007). Gilbert et al. (2008) states that climate change would almost certainly influence the AI virus transmission cycle, and directly affect virus survival outside the host.

In terms of vectors, there has been considerable effort investigating how the HPAI virus enters into unaffected countries. The main identified pathways are wild bird migration, wild bird trade and poultry/ poultry products transport (Chen al. 2005; Ward et al. 2008a; 2008b; 2009; Peiris et al. 2007). In addition, as a zoonotic disease, human travel and infection provides another possible channel for HPAI introduction. Capua and Alexander (2004) and Gilbert et al. (2008) argue that climate change would lead to alterations in wild bird migratory paths.

Considerable circumstantial evidence from Europe, Russia and Mongolia indicate that wild birds played a significant role in AI spread (Gilbert et al. 2006; Irza 2006). Kilpatrick et al. (2006) and the European Food Safety Agency (2006) both conclude that most of the HPAI introductions to Europe were via wild bird migration movements. Peiris et al. (2007) mainly attributes the increased outbreak frequency to the fast expanding, intensive poultry industry as well as greater movement of live poultry and poultry products. Ward et al. (2008a; 2008b; 2009) analyze the HPAI cases in Romania and conclude that the environment and landscape (specifically the Danube River Delta) played a critical role in introduction and initial spread. They also indicate that the movement of poultry might have introduced the infection into central Romania during spring 2006.

Studies in Thailand, Vietnam, Indonesia and China provide other insights, suggesting that human infection and poultry outbreaks are enhanced by several risk factors, including population density, poultry density and local/environmental factors like the incidence of rice paddy fields, water sources, transportation and precipitation (Yupiana et al. 2010; Gilbert et al. 2008; Tiensin et al. 2009; Pfeiffer et al. 2007; Fang et al. 2008; Paul et al. 2010; Hogerwerf et al. 2010).

Results in Fang et al. (2008) indicate that distance to the nearest main city, and distance to the nearest body of water and distance to the nearest highway contribute to the spread of the disease. They also find that higher levels of annual precipitation have a negative effect on outbreak risk. Yupiana et al. (2010) analyze data from Indonesia and find that the number of HPAI outbreaks increases when poultry density or road density increases. Paul et al. (2010) show a progressive increase in HPAI risk with an increase in poultry density for both chickens and ducks, and they also find that areas located near major cities and highway junctions constitute “hot spots” for HPAI risk. Hogerwerf et al. (2010) conduct a global study and find that maximum temperature has significant effects, but that it was much less important than agro-ecological and socio-demographic factors.

HPAI outbreaks have received worldwide attentions and previous studies have examined factors that may contribute to the risk and the spread of HPAI outbreaks. However, there are three limitations in these studies,

- Most neglected climate factors focusing on geographic and social-economic characteristics rather than temperature and precipitation;
- Few studies have examined the relationship between climate factors/climate change and the HPAI outbreaks across the totality of seasons and locations.
- These studies have not addressed the economic loss associated with climate change.

This study extends previous studies addressing the shortcomings identified above plus examines the consequences of climate change as realized in the last 20 years and as projected.

Model and Data

We first present statistical models for the probability of HPAI outbreaks, then describe the data used in the estimation of the proposed models.

Econometric model

We will estimate a relationship between the probability of HPAI outbreaks, a number of regional climate factors and other production characteristic plus the lagged probability of outbreaks. This is done using the basic functional form,

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

where

y_{it}^{*} is the latent dependent variable. Instead of observing y_{it}^{*}, we observe only a binary variable indicating the sign of y_{it}^{*},

$$y_{it} = \begin{cases} 1 & \text{if } \ y_{it}^{*} > 0 \\ 0 & \text{if } \ y_{it}^{*} \le 0 \end{cases}$$

and y_{it} indicating whether a region i had any outbreaks in time period t.

x_{it} is a vector of independent, contemporaneous explanatory variables and including the following:

- Mean temperature and total precipitation
- Squared precipitation due to the conflict results in previous literature (Animal Health Australia 2005; WHO 2007; Fang et al. 2008)
- Seasonal dummies with season fall as the base: In the northern hemisphere, AI infection rates are higher during the spring and fall migration periods (Krauss et al. 2004)
- Dummies of reflecting temperature extremes: HPAI viruses can survive for long periods in the environment, especially when temperatures are low (WHO 2006).

According to Shahid et al.(2009), avian influenza virus H5N1 retained its infectivity at 4°C for more than 100 days and virus lost its infectivity after 24 hours when kept at room temperature (28°C). Thus two temperature indices are constructed. Cold_Month is 1 when the mean temperature is lower than 4oC, and zero otherwise; Similarly, Hot_Month is 1 when the mean temperature is higher than 28oC and zero otherwise

- A flyway index indicates whether a country is on the flyway of wild birds' migration with one and zero otherwise.
- A distance index indicates the distance of each region to the Qinghai Lake in China and nominated the longest distance as 1
- Variables of country characteristics include per capita gross domestic product (GDP), the density of chicken production and the density of total population.
- Interactions of agro-ecological dummies with climate factors (temperature and precipitation)

$y_{i,t-1}$ is the lagged dependent variable allowing the current outbreak probability to be altered by whether the region has incurred previous outbreaks;

c_i is the unobserved effect and is allowed to be correlated with some elements of x_{it};

and $e_{it} \mid (x_i, y_{i,t-1}, ..., y_{i1}, c_i) \sim Normal(0,1)$.

Without loss of generality, we reset 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} as,

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

However, to estimate β and ρ consistently, we need to address the initial conditions problem by making an additional assumption of c_i, that is, how to treat the initial observations, y_{i0}. Wooldridge (2002; 2005) indicate that under the assumption of $c_i \mid (y_{i0}, x_i) \sim Normal(\zeta_0 + \zeta_1 y_{i0} + x_i\zeta, \sigma_a^2)$, we can specify the density in such a way that can be estimated using the standard random effects Probit estimation,

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

where $a_i \mid (y_{i0}, x_i) \sim Normal(0, \sigma_a^2)$ and is assumed not to depend on x_{it}. To avoid too many dimensions in estimation[ii], we use $\overline{x}_i$ to replace of x_i (Chamberlain 1980), which is the average of x_{it} for $t = 1, 2, ...T$. Also to identify time dummies, which do not vary across i, they must be omitted from $\overline{x}_i$ by setting $\zeta = 0$. In turn then the dynamic unobserved effects Probit model arises,

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

where the a subscript means that a parameter vector has been multiplied by $(1 + \sigma_a^2)^{-1/2}$. In turn, this will be used to estimate the HPAI outbreak model.

Data

The statistical analysis will be carried out over monthly outbreak incidence data across 90 regions in 16 countries that 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 FAO fact sheet (Newman et al. 2010).

We define regions as part of a country and large countries have more regions than small countries. For exmample, there are 18 regions in China and 9 regions in the United States. Table 1 lists mean temperature, precipitation and total AI outbreaks in each region and in the corresponding country. We could see that China, South Korea, Japan and the United States have less AI outbreaks compared to other countries in past five years.

The 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 period from January, 2004 to December, 2008. The AI outbreak incidence is a dummy variable where a one indicates whether a region had at least one HPAI outbreak in a given month and zero otherwise;

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 degree Celsius, and the total precipitation including rain and/or melted snow was computed in millimeter.

Data on country characteristics are also used. We include per capita gross domestic product (GDP), the density of chicken meat production and the density of total population in each county by each year. We obained these data for each country from the World Bank, the Food and Agriculture Organization of the United Nations, the United Nations Statistics Division and the USDA Economic Research Service (ERS), respectively.

Agro-ecological conditions with be controlled for with countries grouped into five niches following Hogerwerf et al. (2010). These niches are defined based on

- the level of chicken productivity and
- purchasing power per capita and
- the density of duck and chicken population

Table 2 shows the agro-ecological characteristics of each niche and their corresponding countries/regions falling into each. As we want to see how climate conditions could affect AI outbreaks in a specific agro-ecological zones.

According to Newman et al. (2010), China, Egypt, Nigeria, Germany, Turkey and Russia are key destinations for wild bird migration, so we define the flyway dummy equal to 1 for these countries and set it to zero otherwise. We also measure the approximate distance from Qinghai Lake in China to each region from Google Maps since Qinghai Lake is one of the major wild bird mortality points and there have been over 6,000 migratory wild birds that were found dead with AI since 2005 (Newman et al. 2010).

This study focuses on HPAI outbreaks occurred from January 2004 to December 2008, which captures a significant period of HPAI epidemic activity in Southeast and Central Asia, Africa and Europe. Figure 1 portrays the number of HPAI outbreaks for poultry from January, 2004 to December, 2008 reported to the World Organization for Animal Health (OIE). The data show 7984 outbreaks in poultry flocks plus that the confirmed HPAI number of related human illness and death cases since 2003 are 507 and 302, respectively.

Table 3 provides definitions on the variables[iii]. Figure 2 shows the computed probability of outbreaks across regions based on historical data suggesting that there exists hetrogeneity across regions. The trend in HPAI outbreaks across regions between 2004 and 2008 is shown in figure 1[iv] and 12% of the regions have had HPAI outbreaks in the past 5 years.

When applying the econometric model to our data, the empirical model for estimation is,

$$
\begin{aligned}
P(\mathrm{AIOtbkProb}_{it} = 1 \mid x_{it}) = \Phi(&\zeta_{0a} + \rho_a \mathrm{AIOtbkProb}_{i,t-1} + \beta_{1a} temp_{it} + \beta_{2a} precip_{it} + \beta_{3a} precip\_sq_{it} \\
&+ \textstyle\sum_{j=1}^{4} \beta_{4aj} index_{ij,t} + \displaystyle\sum_{s=1}^{3} \beta_{5as} season_{is,t} + \beta_{6a} ckden_{it} + \beta_{7a} gdpden_{it} + \beta_{8a} popden_{it} \\
&+ \sum_{k=1}^{4} \beta_{9ak} niche_{ik} \cdot temp_{it} + \sum_{l=1}^{4} \beta_{10al} niche_{il} \cdot temp_{it} \\
&+ \zeta_{1a} y_{i0} + \zeta_{2a} \overline{temp}_i + \zeta_{3a} \overline{precp}_i + \zeta_{4a} \overline{precp_i^2} + \textstyle\sum_{m=1}^{2} \zeta_{5am} \overline{index}_i \\
&+ \zeta_{6a} \overline{ckden}_i + \zeta_{7a} \overline{ppden}_i + \zeta_{8a} \overline{gdpden}_i \\
&+ \sum_{q=1}^{4} \zeta_{9aq} \overline{niche_{iq} \cdot temp_i} + \sum_{p=1}^{4} \zeta_{10ap} \overline{niche_{ip} \cdot precip_i})
\end{aligned}
$$

Following Wooldridge (2002), we can consistently estimate $\zeta_{0a}, \beta_a, \rho_a, \zeta_{1a}$ and ζ_a by using a random effects Probit regression and conditional Maximum likelihood Method (MLE). Also following Wooldridge (2002;2005), average partial effects (APE) can be estimated by using the average across i of

$\hat{\beta}_{aj}\phi(\hat{\zeta}_{0a} + x_{it}\hat{\beta}_a + \hat{\rho}_a y_{i,t-1} + \hat{\zeta}_{1a} y_{i0} + \overline{x}_i \hat{\zeta}_a)$ for continuous variables and taking the difference of values at two different x_{jt} for discrete variables, i.e.

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

.

Results

The results involve the regression coefficients, the predicted outbreak probabilities and economic losses associated with climate change.

Estimation results

The estimated coefficients and average partial effects are shown in table 4. To compare, we also report results from a linear probability model with fixed effects. The estimated coefficient for temperature is negative and statistically significant suggesting that outbreak probability decreases as temperatures rises. In particular, a 1^{o}C temperature rise reduces the outbreak probability by 0.22%. In terms of precipitation, we find the estimation results show an inverted-U shape, however, the effect of squared precipitation is insignificant meaning that as precipitation increases, the probability of AI outbreaks increases by 0.34%.

In terms of the other parameters, we also find the outbreak risk increases in winter by 3% when compared with the fall season, perhaps due to the times when the migratory birds are in residence. Nevertheless, these results are consistent with findings from Animal Health Australia (2005) and WHO (2007).

Results also show that the density of total population and chicken production in a country has a statistically and significantly positive effect on the AI outbreak probability and the risk of AI outbreak is lower in countries with higher GDP level. As found by Hogerwerf et al. (2010), the probability of AI outbreaks is highly correlated with chicken production level, density of total population and the development level. There is a higher risk of AI outbreaks in regions/countries with a higher density level of chicken production as well as total population, and most of these are economically poor regions.

We also detect the effect of past outbreaks on the chance of a current outbreak finding a positive significant effect. This indicates that a region with a previous outbreak has an increased chance of a repeat event. The speed at which this effect dies out is portrayed in figure 3 where we see that a previous AI outbreak affects subsequent outbreak probabilities for 5-6 months. The example of HPAI H5N1 outbreak in Hong Kong in 1997 and later in 2003 suggests that H5N1 was still circulating at least among domestic poultry during the prior year (Elvander 2006). The dynamics of how AI survives is important for a country's decision of whether to implement disease prevention and control strategies.

Since it is difficult to distill out the effects of particular variables given the presence of interaction terms, we calculate the average partial effects of each individual item and plot them across niches following Ai and Norton (2003) and Norton, Wang and Ai (2004). Figure 4 shows the average partial effects of temperature and precipitation on

AI outbreaks across niches, respectively, and only reports those that are significant at 10% confidence level.

These results show that the average partial effect of precipitation in niche 5 is negative, meaning that a niche with the lowest density of chickens and duck population is less likely to have an outbreak. In the niches, excepting niche 3, the effects of temperature on AI outbreaks are insignificant. A lower risk of AI outbreaks is related to a higher level of per capita income level. These results are also found in our estimation results.

For most significant variables, the linear probability model with fixed effects gives similar results, however, it is poor in fitting our data because the residual standard error is much smaller than that from the Probit model with random effects, therefore, we will use results from the Probit model in the following studies.

Calculated Outbreak Probabilities

Using results from the Probit regression model, we predict the probability of AI outbreaks in each country which is shown in the second column of table 5. These predicted probabilities based on current climate conditions are consistent with our observed probabilities, for example, Egypt, Indonesia, Thailand, Vietnam, Cambodia have a higher risk of AI outbreaks. In contrast, Japan, South Korea and the United States have a lower probability to have AI outbreaks under current climate condition. However, whether these probabilities would alter under past or future climate change is unknown. Given climate change, countries facing significant changes of temperature and/or precipitation probably encounter a higher risk of AI outbreaks. If this is the case, they could make disease prevention and control plans ahead to minimize disease outbreak costs. In this sense, a national evaluation would be more attractive.

Effects of Climate Change and Associated Economic Loss

Using the estimation results from the Porbit regression model, we now look at climate change effects. In this case, we will 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?
- What would be the additional economic losses due to past and future climate change?

Past climate change contributions to current outbreaks

Based on historical records, the IPCC estimates that the global average temperature has increased by 0.55°C per decade from 1970-2006 (IPCC 2007a). Changes in overall precipitation amounts vary by regions, but it is likely that 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 et al. 2003; Groisman et al. 2004). Since the probability of AI outbreaks is affected by temperature and precipitation according to our regression results, it seems that past climate change may enhance the severity of current AI outbreaks.

We use the observational climate data from the IPCC 2007 date back to 1971-1980. Table 5 reports the annual averaged temperature (^{o}C/ day) and precipitation (mm/ day) in each country. Compared with current mean temperature and precipitation in the northern hemisphere, climate in the past has a lower temperature in all countries except Vietnam, while countries in both lower and higher latitudes have heavier precipitation and countries in middle latitude have less precipitation.

Controlling all other variables and using the new temperature and precipitation data derived above, we simulate the probability of AI outbreaks for past climatic conditions. Table 6 shows these probabilities for each country. Other than Vietnam, changes of temperature and precipitation in past 20 years have increased the risk of AI outbreaks in all countries. Climate change has significantly increased the probability of AI outbreaks by 8% to 1160%. These results suggest that climate change is one of the forces driving the recent increase in outbreaks observed.

If AI disease occurs in more than one region, the situation would be more serious. We plot the AI outbreak distribution across all 90 regions in figure 5. The results show the mean probability of AI outbreaks in all regions would be 0.077 under past climate conditions and 0.116 under current climate, indicating that past climate change has increased the overall mean probability of AI outbreaks by 51%.

Projected climate change contributions to future outbreaks

For our future projections, we select three climate models according to IPCC (2007a), including

- The Hadley Center Coupled Model (Had-CM3), which is a stable global mean climate (Collins et al. 2001) and is a mid-sensitivity case (Schlenker et al. 2006).
- The coupled atmosphere-ocean Climate Model of the Centre National de Researches Meteorologiques (CNRM-CM3), which achieves a reasonable simulation of present-day climate and simulates a general increase in precipitation throughout the twenty first century (Douville et al. 2002).
- The coupled climate model runs at the Geophysical Fluid Dynamic Laboratory (GFDL-CM2), 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).

Since the simulated warming over a short time period (i.e. by 2030) is not very sensitive to the choice of scenarios across the IPCC Special Report on Emission Scenarios (SRES) set (IPCC 2007a), we choose the projected changes of temperature and precipitation under the A1B emission scenario, because it is the medium scenario with respect to the prescribed concentrations and the resulting radiative forcing, relative to the SRES range (Nakicenovic et al. 2000; IPCC 2007a).

Through the IPCC Data Distribution Center (DDC), we obtained the projected changes of temperature and precipitation between 2011 and 2030[v] for each climate model as summarized in Columns 2 to 6 in table 5. Consistent with past observational data, nearly all models project increased temperature and heavier precipitation in middle latitudes, while higher temperature and less precipitation in lower and higher latitudes. In turn, the last three columns of table 6 show the probability changes of AI outbreaks under future climate change.

For most countries, future climate change is found to increase the risk of AI outbreaks. China, Malaysia and the United States have a higher probability of disease outbreaks under future climate change. This occurs partly because these countries produce a high proportion of poultry meat or products and would be easily impacted by AI outbreaks. However, whether these countries are vulnerable to animal disease depends on their adaptation capability. 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.

Nevertheless, on average, the risk of AI outbreaks increases as future temperature and precipitation changes. Specifically, the probability of AI outbreaks across all regions under future temperature and precipitation condition is 0.121, 0.120 and 0.119 under three climate models and it will increase by 3% - 4% under future climate change.

Associated economic loss due to climate change

Since different countries have different contributions of poultry production to their total Gross Domestic Product (GDP), we calculated the additional economic loss by applying the changes of the outbreak probability under climate change to the countries we studied. Before reporting results, we assume,

- When an outbreak occurs that 12% of the domestic birds in each region die from the AI disease or are killed to prevent its spread (following assumptions in the

World Bank report by Burns et al. 2008). We use this percent to calculate the GDP reduction of a further AI outbreak due to climate change

- We calculate the percentage of poultry production to the total GDP in each country in 2008 ($percent_i$) and assume these percentages keep constant in each country over years.
- The real projected GDP values from the World Bank in 2008 and in 2030 can be offset by the poultry loss percent times the GDP share of poultry.

To evaluate the economic loss, we first calculate quantities of interest. For each country i, we assume p_{1i} is the difference between past and current probability of AI outbreaks and p_{2ij} is the difference between the current and future probability with $j = 1, 2, 3$ indicating each climate model.

For the additional economic loss due to past climate change, we have,

$Loss_{pasti} = GDP_{2008i} \cdot p_{1i} \cdot 12\% \cdot percent_i$ for $i = 1, ..., 16$

We have similar equations for economic loss due to future climate change,

$Loss_{futurei} = GDP_{2030i} \cdot p_{2ij} \cdot 12\% \cdot percent_i$ for $i = 1, ..., 16$ and $j = 1, 2, 3$

Table 6 reports the resultant estimates of GDP loss due to past and future climate change. Generally speaking, additional GDP losses occur across the countries and past climate change generally causes a larger economic loss because of a lower probability under future climate change. Developed countries, such as South Korea and Japan, had smaller losses relative to their total GDP. On the other hand, some developing countries in Asia with a small economy, such as Indonesia, Thailand, and Cambodia were exposed to a high proportion of losses. Additionally, many countries in our sample have reported more than one AI outbreaks since 2003, so the expected economic loss due to past climate change could be larger because of a higher frequency of outbreaks.

The United States is the world's largest producer and second largest exporter of poultry meat with totals over 43 billion pounds annually and the total farm value of US poultry production exceeds $20 billion. Therefore, any further outbreak of HPAI in United States or other countries could hurt the benefits of poultry industry in the United States. Our estimation suggest that past climate change in the United States costs additional $29 million and the additional economic losses will reach $12-$18 million because of future climate change.

In past five years, only Texas had one AI H5N2 case of poultry in 2004 and other states were free of AI, so we evaluate the expected economic loss of Texas separately. The estimated economic loss of Texas is about $2.7 million because of past climate change. Egbendewe-Mondzozo et al. (2009) estimate that the economic losses of H5N2 outbreak in three districts in Texas without vaccination, demand shocks and trade ban are $121 million. Our result indicates about 2.2% of the economic loss in Texas were due to past climate change.

Since China has several AI outbreaks in past few years, it would be interesting to partition out the economic losses caused by climate change. Table 7 shows that the additional economic losses in China due to past climate change are about $107 million, while costs fall in a range of $105-$146 million because of future climate change.

In addition to a national level analysis, we also compute GDP losses by region. Figure 6 shows that total economic losses due to past climate change are larger than that caused by future climate change if less than 15 regions have AI outbreaks at the same time, while future climate change causes more economic loss if more than 15 regions have AI outbreaks.

As shown in figure 5, the probability of more than 20 regions having AI outbreaks at the same time is very low and most countries in this study have at least one region but no more than 18 regions, so the additional losses in a country are highly related to how many regions are affected by AI disease and it is more important for countries with more regions to implement disease prevention and surveillance plans as well as climate change adaptation strategies to minimize total economic loss of a future outbreak of AI under climate change.

Concluding Remarks

We examined the relationship between climate conditions and the spread of AI and evaluated the effects of past and projected climate change on the probability of AI outbreaks. The estimation results show climate plays an important role in the spread of AI outbreaks. The risk of AI outbreaks will decrease as temperature rises, however, it will increase because of heavier precipitation. Therefore, the overall effects of temperature and precipitation on AI outbreaks are depending on climate conditions in each region as well as in each country.

Under the same climate condition, regional characteristics also contribute to the spread of outbreaks. Regions with higher density of duck and chicken population face a higher risk of outbreaks. Outbreak risks are lower in regions with higher levels of poultry productivity per operation and regional income.

Overall, the outbreak risk is increased in areas with lower temperature and heavier humidity. These areas, moreover, are associated with large agriculatural and poultry populations, low productivity of chicken, and in most cases are economically poor regions. Surveillance and other control measures would be advised to emphasize such regions. This also indicates that warmer and wetter conditions under climate change may be contributing to the recent rapid spread of outbreaks and that climate change as it progresses may worsen the problem.

It is evident that past climate change has enhanced economic loss from AI outbreaks and caused substantial costs in most countries. On the other hand, effects of future climate change differ across regions; some countries may even gain under future climate change.

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Table l Total AI Outbreaks, Mean Temperature and Precipitation in Each Region

Country	Region	Total AI outbreaks (numbers)	Temperature (^oC)	Precipitation (mm)	Country	Region	Total AI outbreaks	Temperature (^oC)	Precipitation (mm)
China	1	0	13.11	39.06		46	80	21.55	108.89
	2	1	17.60	94.12		47	189	25.87	173.59
	3	4	7.19	29.97		48	1135	27.59	190.16
	4	6	8.76	63.45	Pakistan	49	22	24.67	26.13
	5	1	6.78	50.68		50	3	25.01	51.63
	6	0	5.81	43.44		51	23	26.95	25.31
	7	1	16.54	85.34		52	26	21.83	99.57
	8	7	16.59	80.54	South Korea	53	3	11.58	121.84
	9	0	20.63	127.48		54	3	14.53	20.80
	10	4	18.73	126.27		55	2	12.98	114.95
	11	0	14.89	77.27		56	1	14.68	107.15
	12	13	17.82	100.43		57	1	14.72	88.13
	13	6	18.41	117.23	Japan	58	2	12.19	128.92
	14	12	24.12	158.64		59	5	17.60	167.79
	15	2	21.74	97.69		60	4	16.25	112.83
	16	6	14.58	93.99		61	1	16.73	82.33
	17	1	18.28	90.72		62	2	9.39	87.46
	18	5	14.01	45.20	Malaysia	63	15	27.68	244.67
Egypt	19	209	20.83	127.38	Cambodia	64	24	28.56	18.38
	20	120	22.26	0.25	Germany	65	493	11.00	0.00
	21	489	22.50	1.83	Romania	66	39	9.31	60.40
	22	415	21.56	0.00		67	27	10.55	47.25
	23	18	25.52	0.12		68	39	11.89	44.26
	24	10	27.04	0.15		69	5	11.35	53.45
	25	4	22.82	0.05	Russia	70	125	3.92	0.00

Nigeria	26	21	27.62	26.88		71	89	12.16	1.95
	27	112	27.24	10.40		72	1	12.20	4.03
	28	71	27.61	56.06		73	16	6.53	0.00
	29	92	28.01	2.57		74	3	12.00	0.00
Indonesia	30	571	27.22	140.22	Turkey	75	9	18.30	39.29
	31	36	27.17	155.68		76	83	10.19	38.85
	32	58	28.05	94.21		77	18	11.32	27.23
	33	1360	26.89	127.47		78	43	13.23	32.25
	34	20	26.54	193.00		79	16	14.35	35.70
	35	74	27.05	69.82		80	3	18.38	42.93
	36	9	26.54	193.00		81	53	15.91	34.81
Thailand	37	299	29.09	138.05	United States	82	0	8.42	102.58
	38	38	27.13	136.46		83	0	7.11	69.25
	39	54	25.77	110.42		84	0	12.49	95.30
	40	70	27.37	121.21		85	0	17.43	102.75
	41	227	27.79	122.28		86	0	7.04	37.68
	42	17	27.80	123.61		87	1	17.24	78.94
Vietnam	43	531	23.75	137.44		88	0	11.79	30.26
	44	122	23.88	126.82		89	0	8.68	56.00
	45	265	23.84	145.49		90	0	13.38	33.24

Table 2 Agro-ecological Characteristics of Niches

	CPP[(a)]	PPPC[(b)]	DAP[(c)]	Regions/Countries
Niche 1	2	2	4	Thailand, Vietnam, Malaysia, Shaanxi, Sichuan, Liaoning, Jilin, Jiangxi, Guangxi, Guizot, Shandong, Anhui, Heilongjiang Hubei
Niche 2	1	1	3	Russia, Indonesia, Pakistan, Inner Mongolia
Niche 3	3	4	3	Cambodia, Nigeria, Turkey, Romania
Niche 4	4	4.5	5	Egypt, Guangdong, Shanghai, Beijing, Hunan, Jiangsu, Fujian
Niche 5	5	5	1	Japan, South Korea, Germany, US

Note: (a) CPP indicates the level of chicken production productivity;

(b) PPPC indicates the level of purchasing power per capita;

(c) DAP indicates the density of duck and chicken populations;

A number from 1 to 5 indicates the level or density of this measure in this country with 1 being the lowest and 5 the highest.

Table 3 Definitions of Variables

Variable	Definition
AIOtbkProb	Outbreak incidence in a country and month equaling 1 if outbreaks occured,0 otherwise
Temp	Mean temperature (^oC)
Precip	Total precipitation in mm
Precip _sq	Squared total precipitation
Spring (season1)	Dummy variable for whether this is a spring month in March-May
Summer(season2)	Dummy variable for whether this is a summer month in June-August
Winter(season3)	Dummy variable for whether this is a winter month in December-February
Niche1*temp	Interaction of Niche 1 dummy and temperature
Niche3*temp	Interaction of Niche 3 dummy and temperature
Niche4*temp	Interaction of Niche 4 dummy and temperature
Niche5*temp	Interaction of Niche 5 dummy and temperature
Niche1*precip	Interaction of Niche 1 dummy and precipitation
Niche3*precip	Interaction of Niche 3 dummy and precipitation
Niche4*precip	Interaction of Niche 4 dummy and precipitation
Niche5*precip	Interaction of Niche 5 dummy and precipitation
Cold_Month (index1)	Dummy variable for whether this month average temperature is <= 4^oC
Hot_Month (index2)	Dummy variable for whether the month average temperature is >= 28^oC
Flyway(index3)	Dummy variable for whether on the flyway
Distance(index4)	Distance from each region to Qinghai Lake in China
Log(ckden)	Logged chicken density
Log(ppden)	Logged total population density
Log(gdpden)	Logged per capita GDP

Table 4 Regression Results from the Probit Model and Linear Probability Model

	Probit Model with Random Effects		Linear Probability Model with Fixed Effects
Variables	Coefficient	APE	Coefficient
$AIOtbkProb_{i,t-1}$	1.4257***	0.3233***	0.4063***
	(0.0682)	(0.0262)	(0.0296)
Spring (season1)	0.1020	0.0116	0.0093
	(0.0834)	(0.0098)	(0.0104)
Summer (season2)	0.0589	0.0066	0.0052
	(0.0926)	(0.0106)	(0.0101)
Winter (season3)	0.2436***	0.0294***	0.0391***
	(0.0944)	(0.0127)	(0.0118)
Temp	-0.0202*	-0.0022*	-0.0018
	(0.0115)	(0.0013)	(0.0012)
Precip	0.0308*	0.0034*	0.0064**
	(0.0184)	(0.0020)	(0.0025)
Precip_sq	-0.0007	-0.0001	-0.0001***
	(0.0004)	(0.0001)	(0.0000)
Cold_Month (index1)	-0.2538	-0.0236	-0.0230
	(0.1687)	(0.0133)	(0.0146)
Hot_Month (index2)	0.0304	0.0034	-0.0086
	(0.0948)	(0.0107)	(0.0142)
Flyway (index3)	0.0307	0.0034	
	(0.1571)	(0.0172)	
Distance (index4)	0.0771	0.0084	
	(0.3938)	(0.0429)	
Log(ckden)	0.7672*	0.0835*	0.1349**
	(0.4565)	(0.0500)	(0.0604)
Log(ppden)	8.4990***	0.9254***	1.4132***
	(2.4085)	(0.2667)	(0.4290)
Log(gdpden)	-1.1596**	-0.1263**	-0.1457**
	(0.5873)	(0.0641)	(0.0562)
Niche1*Precip	-0.0119	-0.0013	-0.0042
	(0.0183)	(0.0020)	(0.0029)
Niche3*Precip	-0.0380	-0.0041	-0.0097**
	(0.0424)	(0.0046)	(0.0045)
Niche4*Precip	0.0263	0.0029	0.0026
	(0.0262)	(0.0029)	(0.0026)
Niche5*Precip	-0.1348**	-0.0147**	-0.0059***
	(0.0676)	(0.0072)	(0.0023)

Niche1*Temp	0.0033	0.0004	0.0012
	(0.0133)	(0.0015)	(0.0011)
Niche3*Temp	-0.0292*	-0.0032*	-0.0009
	(0.0161)	(0.0017)	(0.0015)
Niche4*Temp	-0.0026	-0.0003	-0.0007
	(0.0152)	(0.0017)	(0.0017)
Niche5*Temp	0.0104	0.0011	0.0019*
	(0.0163)	(0.0018)	(0.0011)
Constant	-4.5280***		-5.3218***
	(1.4093)		(1.9694)
/lnsig2u	-3.0377***		
	(0.3989)		
sigma_u	0.2190***		1.3821
	(0.0437)		
sigma_e			0.2623
rho	0.0457***		0.9652
	(0.0174)		
Residual standard error	0.0701		1.9601
Likelihood-ratio test of rho=0	chibar2(01)=14.52 Prob>=chibar2=0.000		

Asterisk (*), double asterisk (**) and triple asterisk(***) denote variables significant at 10%, 5% and 1% respectively; Standard errors are in parenthesis.

Table 5 Past and Projected Climate change

Country	Changes of climate in 2011-2030 (SRA1B)						past climate of 1980		current climate	
	CNRM:CM3		HAD:CM3		GFDL:CM2					
	TEMP (^{o}C)	PRECIP (mm)	TEMP (^{o}C)	PRECIP (mm)	TEMP (^{o}C)	PRECIP (mm)	TEMP (^{o}C)	PRECIP (mm)	TEMP (^{o}C)	PRECIP (mm)
China	1.0259	0.0112	1.2820	0.0403	1.0726	0.0079	7.80	41.62	7.80	41.62
Egypt	1.3496	-0.0020	1.2740	0.0092	0.8690	-0.0053	22.31	4.07	22.31	4.07
Nigeria	1.3515	0.1539	1.0374	0.0487	1.0641	0.0429	26.67	63.45	26.67	63.45
Indonesia	0.8388	-0.0434	0.2384	0.7130	0.7849	-0.0627	25.67	227.84	25.67	227.84
Thailand	0.9248	0.0064	0.9262	-0.3882	0.7516	-0.1581	25.85	154.69	25.85	154.69
Vietnam	0.8800	-0.0585	1.0006	-0.1349	0.6944	-0.1303	24.62	149.91	24.62	149.91
Pakistan	1.3024	-0.0342	1.0755	0.0381	1.1433	-0.0375	19.47	20.47	19.47	20.47
South Korea	1.0133	-0.0727	1.1600	0.1401	0.5000	-0.0221	11.28	112.76	11.28	112.76
Japan	1.0795	-0.0548	1.2656	0.1310	0.6532	-0.0620	8.11	102.09	8.11	102.09
Malaysia	0.8514	-0.1701	0.7173	-0.2254	0.8270	0.1147	25.56	238.30	25.56	238.30
Cambodia	0.9567	0.0227	0.9967	-0.1873	0.7613	-0.0861	26.84	153.14	26.84	153.14
Germany	0.8022	0.0790	1.0361	0.0571	1.3289	-0.0460	8.61	56.69	8.61	56.69
Romania	1.0753	0.0857	1.7208	0.0021	1.0407	-0.1165	9.33	55.27	9.33	55.27
Russian	1.1036	0.0243	1.5434	0.0631	1.4028	0.0365	-1.94	44.97	-1.94	44.97
Turkey	1.1263	-0.0178	1.3878	-0.0508	0.7331	-0.0172	11.20	48.32	11.20	48.32
United States	0.8501	-0.0060	1.1002	0.0214	1.1455	0.0184	4.27	55.35	4.27	55.35

Table 6 Predicted Probability under Past and Projected Climate Change

country	Predicted probabilities under climate change					Changes of probability (%) under climate change			
	current	past	Projected (CNRM)	Projected (HAD)	Projected (GFDL)	past	Projected (CNRM)	Projected (HAD)	Projected (GFDL)
China	0.0506	0.0126	0.0572	0.0598	0.0576	300	13	18	14
Egypt	0.2245	0.1883	0.2296	0.2278	0.2190	19	2	1	-2
Nigeria	0.2337	0.1654	0.2362	0.2306	0.2312	41	1	-1	-1
Indonesia	0.3373	0.2512	0.3376	0.3203	0.3362	34	0	-5	0
Thailand	0.1934	0.1300	0.1963	0.1967	0.1923	49	2	2	-1
Vietnam	0.2356	0.2191	0.2376	0.2408	0.2328	8	1	2	-1
Pakistan	0.1556	0.0800	0.1686	0.1639	0.1653	95	8	5	6
South Korea	0.0379	0.0103	0.0345	0.0356	0.0306	268	-9	-6	-19
Japan	0.0217	0.0034	0.0184	0.0192	0.0166	542	-15	-12	-23
Malaysia	0.0938	0.0695	0.1138	0.1115	0.1134	35	21	19	21
Cambodia	0.2838	0.1056	0.2480	0.2490	0.2442	169	-13	-12	-14
Germany	0.0493	0.0186	0.0761	0.0792	0.0834	165	54	60	69
Romania	0.0251	0.0161	0.0255	0.0284	0.0254	56	2	13	1
Russian	0.0523	0.0042	0.0667	0.0719	0.0702	1160	27	37	34
Turkey	0.0483	0.0251	0.0508	0.0525	0.0482	93	5	9	0
United States	0.0121	0.0015	0.0147	0.0158	0.0159	691	22	31	32

Table 7 Associated GDP Loss under Climate Change

	GDP values (in billions of 2005 dollars)			Increased GDP Loss under climate change (in millions of 2005 dollars)			
	2008	2030	% of poultry loss to GDP	past	Projected (CNRM)	Projected (HAD)	Projected (GFDL)
China	3114.33	17604.85	0.0906	107.04	105.03	146.76	111.62
Egypt	119.83	292.24	0.1237	5.37	1.84	1.20	-1.97
Nigeria	110.84	344.17	0.1107	8.38	0.96	-1.16	-0.96
Indonesia	355.24	1110.88	0.1428	43.69	0.48	-2.70	-1.78
Thailand	212.18	541.60	0.1020	13.72	1.62	1.86	-0.59
Vietnam	65.19	261.25	0.1460	1.57	0.78	1.98	-1.07
Pakistan	136.33	328.59	0.0032	0.33	0.14	0.09	0.10
South Korea	953.86	2108.54	0.0272	7.16	-1.97	-1.34	-4.19
Japan	4436.61	5494.59	0.0039	3.16	-0.71	-0.54	-1.08
Malaysia	158.79	378.65	0.1262	4.88	9.57	8.45	9.37
Cambodia	7.14	24.15	0.1655	2.11	-1.43	-1.39	-1.58
Germany	2985.76	4128.62	0.0055	5.05	6.08	6.77	7.73
Romania	125.52	233.13	0.0711	0.80	0.07	0.54	0.06
Russia	973.50	1630.26	0.0625	29.32	14.65	19.89	18.19
Turkey	385.00	917.17	0.0962	8.62	2.15	3.71	-0.08
United States	13228.80	22146.09	0.0208	28.99	12.38	17.11	17.90
Texas	1223.511	1607.37[6]	0.0206	2.66	0.89	1.23	1.29

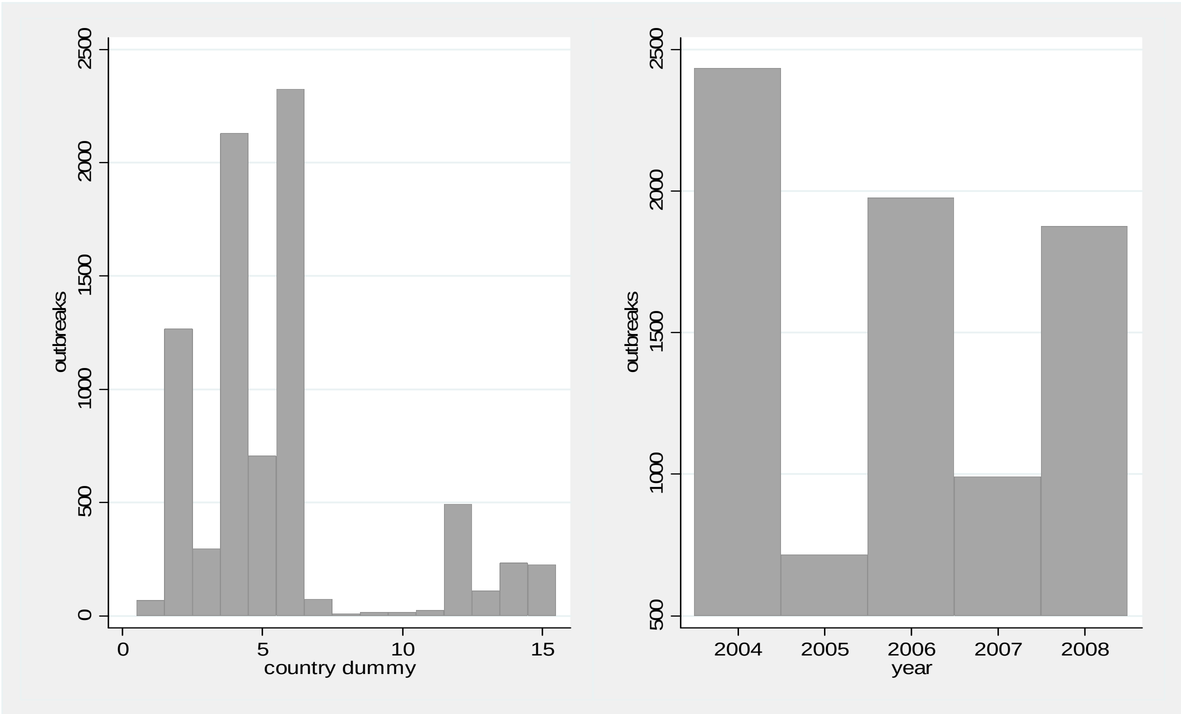

Figure 1 Outbreaks of HPAI H5N1in poultry from Jan, 2004 to Dec, 2008

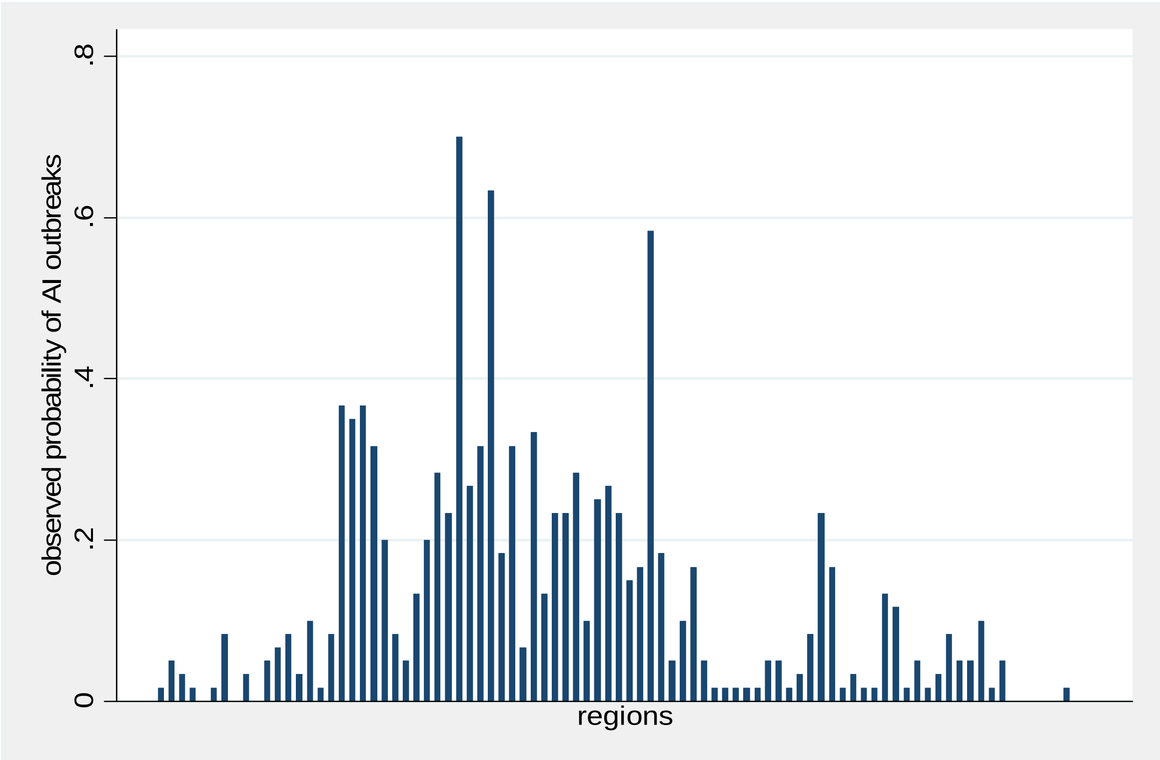

Figure 2 AI Outbreak Probabilities across Region

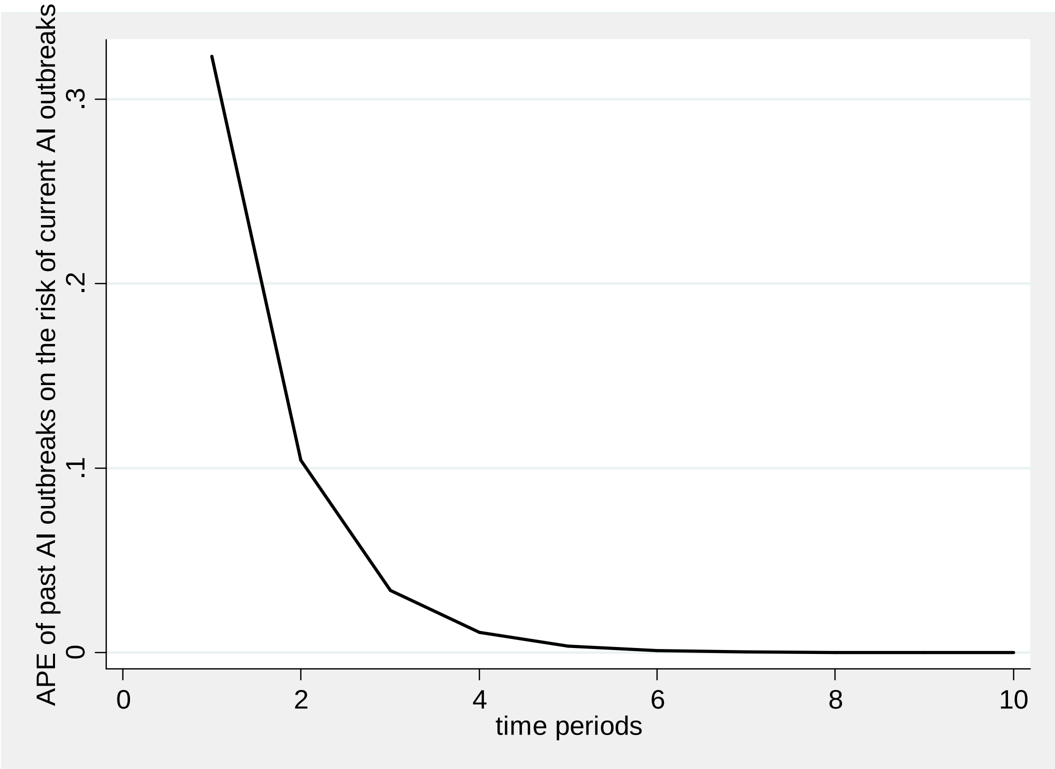

Figure 3 Average Partial Effects of Previous HPAI outbreaks on Current Outbreaks

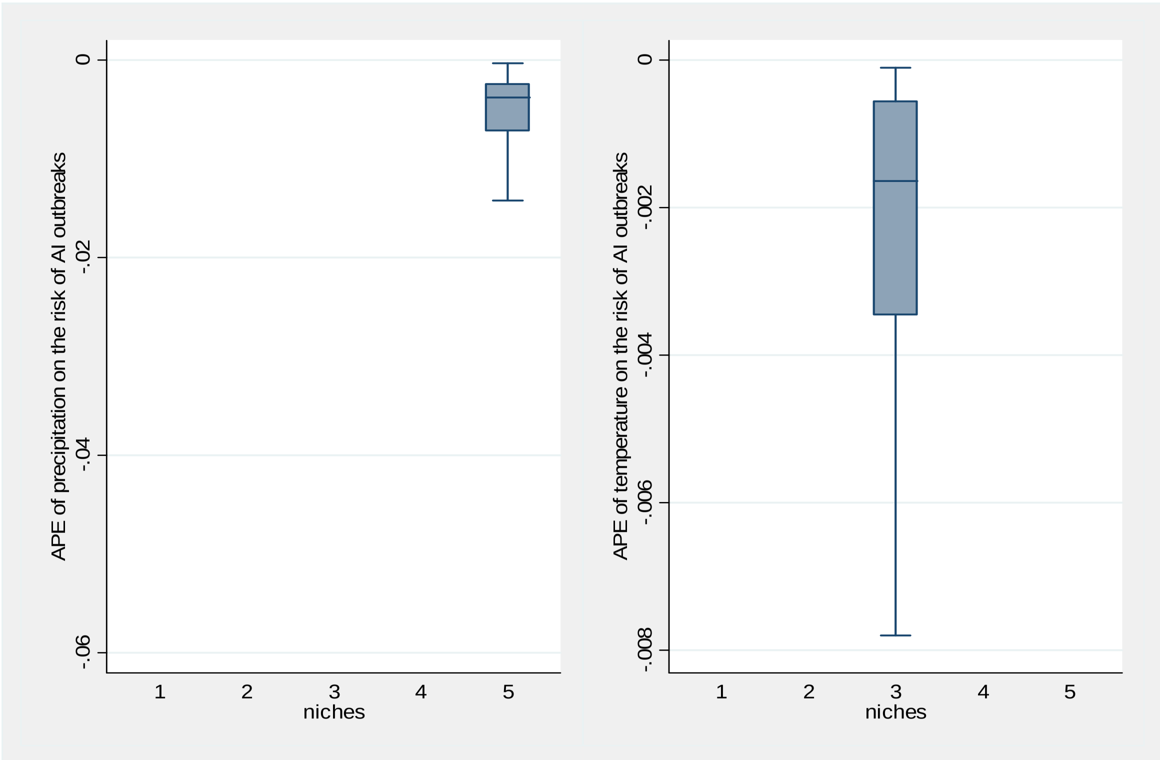

Figure 4 Average Partial Effects of Precipitation and Temperature on AI outbreaks across Niches

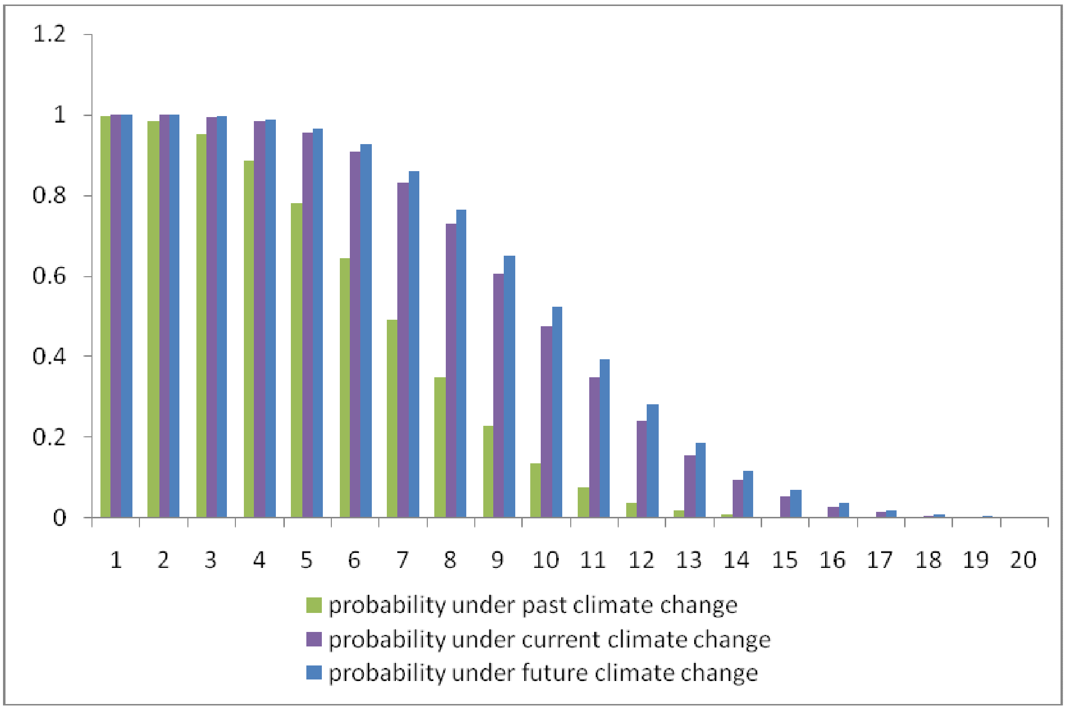

Figure 5 Overall Probability changes under past and future climate change

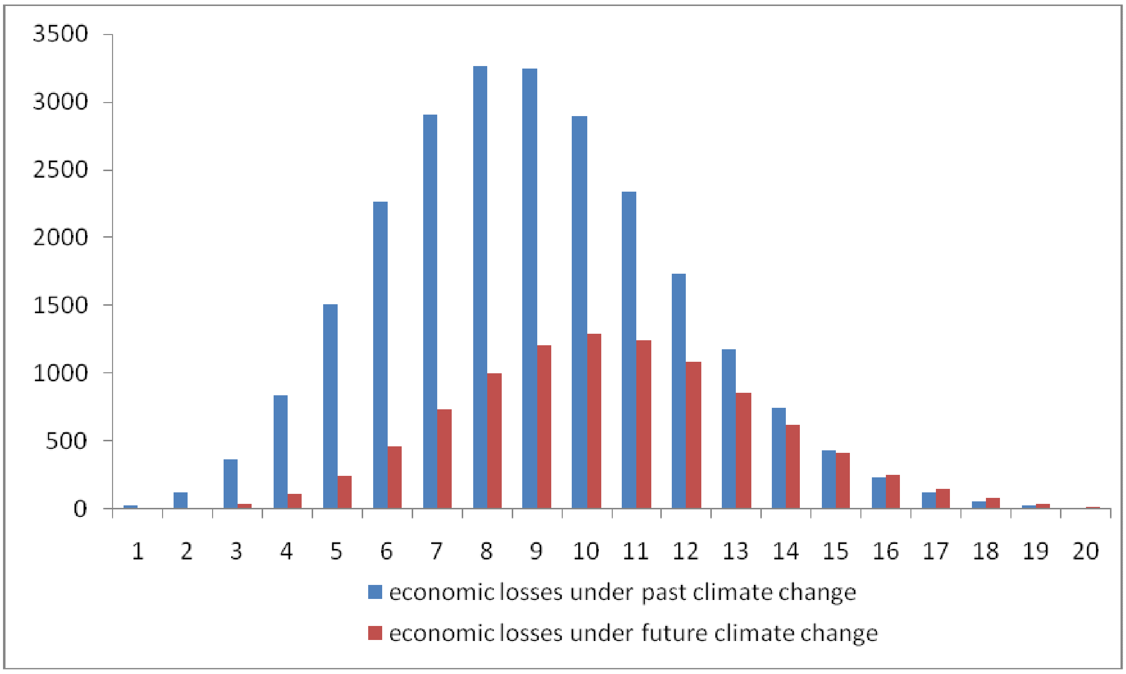

Figure 6 Additional Economic Losses under Climate Change

Appendix

Table 8 Statistical characteristics of variables

Variable	Mean	Std. Dev.	Min	Max
AIOtbkProb	0.12	0.32	0	1
$AIOtbkProb_{t-1}$	0.12	0.33	0	1
spring	0.25	0.43	0	1
summer	0.25	0.43	0	1
winter	0.25	0.43	0	1
temp	18.29	10.30	-21.00	35.69
precip	77.39	112.44	0	2383.54
precip_sq	18629.57	121379.80	0	5681244.00
Cold_Month (index1)	0.12	0.32	0	1
Hot_Month (index2)	0.16	0.36	0	1
Flyway(index3)	0.47	0.50	0	1
Distance(index4)	0.37	0.24	0.06	1
niche1*precip	31.12	81.67	0	1143.00
niche3*precip	6.28	24.02	0	609.09
niche4*precip	8.42	60.18	0	2383.54
niche5*precip	18.35	54.54	0	915.67
niche1*temp	5.65	10.58	-17.66	32.10
niche3*temp	2.99	7.81	-7.10	34.33
niche4*temp	3.06	8.01	-3.74	35.69
niche5*temp	2.86	6.87	-11.39	29.60
Log(ckden)	-0.15	0.85	-2.70	1.29
Log(ppden)	4.68	0.91	2.11	6.18
Log(gdpden)	8.18	1.35	5.93	10.69

[i] A larger number of countries have been affected by the outbreaks of HPAI in past 5 years. A summary of loss evaluation is provided in the following section.

[ii] Since we 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 compared with our sample size.

[iii] Statistical descriptions are reported in Table 8 in the appendix.

[iv] See Table 2 for variable definitions.

[v] We consider that it is impossible for us to project disease outbreaks in a year that is far away from now, so in this paper, we project the situation of disease outbreaks in a short-time period.

[6] According to the World Bank, the growth rate of GDP in United States from 2005 to 2030 would be 2.31, so we project the GDP of Texas in 2030 using its GDP in 2008 and the GDP growth rate of United States.