INTEGRATED ECONOMIC-EPIDEMIC MODELING OF AVIAN INFLUENZA MITIGATION OPTIONS: A CASE STUDY OF AN OUTBREAK IN TEXAS

A Dissertation

by

AKLESSO EGBENDEWE-MONDZOZO

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

December 2009

Major Subject: Agricultural Economics

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ABSTRACT

Integrated Economic-Epidemic Modeling of Avian Influenza Mitigation Options: A Case Study of an Outbreak in Texas. (December 2009) Aklesso Egbendewe-Mondzozo, B.S., Université de Lomé; M.A., Université de Cocody; M.S., Texas A&M University

Chair of Advisory Committee: Dr. Bruce A. McCarl

Recent World Animal Health Organization (OIE) reports on Avian Influenza (AI) outbreaks in Asia, Europe and Canada suggest that there is a nonzero probability that an outbreak may occur anywhere in the world, including the US. To help evaluate possible policy in the face of such an event, this dissertation does an economic evaluation of the implications of using two mitigation strategies: one corresponding to the currently response strategy; and the other an OIE recommended one utilizing vaccination. To do this, the dissertation develops and uses an integrated economic-epidemic model. In this effort, I first estimate the cost of an AI outbreak under a deterministic disease spread assumption where a new vaccination strategy and the current strategy are compared. Subsequently, I introduce risk in the model and construct 95% confidence intervals for the outbreak costs, and I rank the outcomes of the alternative strategies using stochastic dominance criteria. In addition, during both phases, I develop and estimate the

breakeven probability for an event where ex-ante fixed costs of vaccine stockpiling are justified by the reduction in disease event damages.

Results under deterministic disease spread assumption suggest that the vaccination strategy lowers the cost of outbreaks as opposed to the current strategy. This happens because vaccination reduces the number of culled and quarantined flocks. The study is conducted in three locations, yielding the finding that the costs of an outbreak vary depending on the densities of poultry flocks. I also find that when consumer demand shifts due to the outbreak, the costs are much larger. Finally, I find that ex-ante vaccine stockpiling is justified for all the sub-regions if the probability of outbreak exceeds 0.07.

The stochastic disease spread assumption results also show that the vaccination strategy dominates in first degree stochastic dominance sense. Consistent with stochastic dominance results, the 95% confidence intervals have narrower ranges under the vaccination strategy than without it. Finally, the distribution of the breakeven probability for vaccine stocking has a mode of 0.07 and that the probability is accurate with 82% likelihood. However, the threshold varies with the disease transmission parameters and could reach up to 0.32.

DEDICATION

To my wife Catherine, my daughter Debora and my son David, I love them more than they could ever imagine.

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I would like to thank my committee chair, Dr. Bruce A. McCarl, and my committee members, Dr. Levan Elbakidze, Dr. Frederick O. Boadu, Dr. David Bessler, and Dr. Qi Li, for their guidance and for all types of support throughout the course of this research.

Thanks to the United State Department of State and the Institute of International Education (IIE) who provided me with a Fulbright Scholarship that brought me to the United States.

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Finally, thanks to my adopted mother Dana Fujimoto and father Dale Fujimoto for their encouragement and support to my wife for her patience and prayers.

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1. INTRODUCTION

Recent avian influenza (AI) outbreaks and their economic consequences raise concerns about prevention methods, mitigation options and their cost effectiveness. Some of the most recent events include outbreaks in Japan and Korea in January 2004 (Nishiguchi et al. 2005) and outbreaks in numerous countries in 2008 (Nigeria, Benin, Togo, Egypt, United Kingdom and Canada)¹. Historically, the United States experienced several AI outbreaks (Delaware, New Jersey, Maryland and Texas in February 2004). The outbreak in Texas occurred in Gonzales County east of San Antonio. During that outbreak the index flock (6,608 broiler) and 5 live bird markets were depopulated. The outbreak was quickly controlled by the Texas Animal Health Commission (TAHC) within a month and half (Pelzel, McCluskey and Scott 2006).

The spectrum of diseases called avian Influenza involves various combinations of 16 hemagglutinin (H) and neuraminidase (N) proteins subtypes (Pelzel, McCluskey and Scott 2006), which could be classified into high pathogenic and low pathogenic groups based on the ability to cause disease. High pathogenic strains include subtypes H5 and H7, while low pathogenic strains include all of the other subtypes. However, under the right circumstances the low pathogenic strains can mutate into more serious threats (Alexander 2000). Of particular significance are the H5N1 and H5N2 subtypes, which could exhibit mortality rates of 100 percent in poultry and serious illness and even

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

 1 OIE 2009 Update on highly pathogenic avian influenza in animals (type h5 and h7)

death in humans. The virus spreads through direct bird to bird contact as well as through indirect contact via contaminated feed, equipment, water, air and workers.

Even though the disease is zoonotic and presents a threat to humans, US deaths from the highly pathogenic avian influenza (HPAI) among humans have not been observed. Most human deaths have been observed in Asian countries (Vietnam, China, and Indonesia with respectively 5, 3 and 17 deaths in 2008 ². Nevertheless, the economic effect of an outbreak can be quite costly for the poultry industry in particular, and for the economy in general. This study focuses on a potential regional outbreak (In South east Texas) examining the economic consequences for the commercial poultry sector in the United States. Human health implications or considerations for wild bird populations are not examined in this study.

There are two major implications of an AI outbreak for the poultry industry; domestic damages and loss of international markets. Domestically, an AI outbreak would cause losses in production as poultry would be diverted from the market in disease control efforts. Furthermore, the associated risks of human illness could likely cause a perhaps temporary change in consumers' preferences for poultry products. Such events would also cause losses for upstream input suppliers like feed producers. The Domestic implications of an outbreak would heavily depend on the level of preparedness and on quick control. If the outbreak is quickly controlled, consumers' negative reactions and damages in the upstream industries would be minimized. However, quick response at any cost may not be economically effective.

 2 WHO 2009 publication at http://www.who.int/csr/disease/avian_influenza/country/en/

International trade consequences might also be significant. During past outbreaks in the US international trade partners have been observed to ban poultry imports from the affected country or at least a region therein with the ban persisting until that country is declared AI free. For example, after the Gonzales' outbreak, 44 countries imposed import restrictions on either Texas or U.S poultry products (Pelzel, McCluskey and Scott 2006).

Finally unlike other economic impact analysis, economic analysis of the costs of infectious animal disease outbreaks depends not only on economic variables but also on biological disease. Because of these attributes, the cost assessment of a hypothetical outbreak requires interdisciplinary interaction between economists and biological scientists.

1.1 Research Objectives and Methodology

The principal objective of this study is to improve ways of managing animal diseases. In pursuing this objective, this dissertation has a more specific goal that is to conduct an evaluation of whether the use of vaccination is a superior practice to currently recommended policy. In pursuing this goal efforts are devoted to 1) developing an integrated economic-epidemic model of Avian Influenza (AI) that includes disease control and mitigation options, 2) applying the developed model to simulate the case of a hypothetical outbreak in Texas under a deterministic disease spread assumption, and 3) ranking alternative stochastic disease control strategies results using stochastic dominance criteria. More specifically, the study examines the welfare implications of two disease control options:

- the current USDA recommended approach that establishes a quarantine zone in a 5-miles radius around the outbreak site within which every flock is depopulated, and then a varying surveillance radii around that zone plus movement restrictions and testing (Pelzel, McCluskey and Scott 2006); and
- an alternative mitigation strategy which is recommended by the World Animal Health Organization that vaccinates all susceptible flocks in near proximity to the quarantine zone in addition to the current strategy stated above (OIE 2007and 2008)

Both strategies are evaluated under a set of economic and epidemic constraints in the context of Texas commercial poultry operations.

Further, since vaccination use is contingent on the vaccine availability, an exante vaccine investment decision is investigated. Following Elbakidze and McCarl (2006), the critical outbreak probability level for which an upfront investment should be made is determined.

1.2 Organization of the Study

The dissertation is organized as follows. Section one introduces the study and presents the objectives of the study. Section two gives an overview of the literature on the costs of an avian influenza outbreak. The integrated epidemic-economic partial equilibrium model used in the study is also discussed. Section three applies the integrated model to evaluate the cost of a hypothetical outbreak in Texas commercial poultry operations. A decision making criteria and process that calculates the critical outbreak probability level for an upfront investment in vaccines to be economically efficient is also presented.

Section four introduces risk and decision maker risk aversion into the analysis and carries out a risk version of the vaccination study.

2. LITERATURE REVIEW AND AN INTEGRATED ECONOMIC-EPIDEMIC AVIAN INFLUENZA MITIGATION MODEL

Studies on infectious animal disease management generally fall into three classes (1) purely epidemiological (e.g. Bates, Thurmond and Carpenter 2003), (2) epidemiological with some economic implications (e.g. Garner and Lack 1995) or (3) epidemiological with an associated module (e.g. Schoenbaum and Disney 2003). Recent literature reviews of animal disease outbreak impact evaluations (Paarlberg, Seitzinger and Lee. 2005; Pritchett and Johnson 2005) suggested that studies combining integration of economic and epidemic models would improve the quality of the analysis. Examples of integrated animal disease models are given in the papers of Rich and Winter-Nelson (2007) and Carpenter et al. (2007) which studied simulated foot-mouth-disease (FMD) outbreaks. The few published studies that investigate avian influenza (AI) outbreaks (e. g. Paarlberg, Seitzinger and Lee 2007; Djunaidi and Djunaidi 2007, Beach, Poulos and Pattenayak 2007 and Brown et al. 2007) have not used integrated models.

This section outlines an integrated epidemic and economic AI model designed for evaluations of outbreak mitigation strategies and conducting vulnerability and cost assessments. The work by Rich and Winter-Nelson has been extended to include a latent category in our disease spread formulation. Specifically, a Susceptible-Latent-Infected-Removed (SLIR) epidemic model (Elbakidze 2008; Ward, 2007) is used within a partial equilibrium economic model. In particular, the model will be used to evaluate the effectiveness of operating with and without vaccination. Also, a pre-event investment analysis is conducted on prior vaccination investment before the outbreak.

The remainder of the section is structured as follows. Section 1 presents a literature review on economic cost of animal disease outbreaks. Section 2 gives a selected review of empirical methods that have been used in animal disease modeling. Section 3 to section 5 present the theoretical formulation of the integrated epidemiceconomic model of AI mitigation. Section 6 to section 7 discusses some econometric specification issues. Section 8 presents a pre-event post-event decision making model formulation and section 9 concludes this section.

2.1 Background on the Costs of an AI Outbreak

Previous studies have found that economic impacts of animal disease outbreaks in terms of mitigation costs, consumers' and producers' surpluses losses, production losses and international trade losses could be significant (Cupp, Walker and Hillison 2004; Paarlberg, Seitzinger and Lee 2007; CAST 2006).

Cupp, Walker and Hillison (2004) estimated that the U.S 1983-1984 AI outbreaks cost \$63 million and the 2002 case led to a producer loss of roughly \$130- \$140 million. Most AI outbreaks have spillover effects on the non affected regions as well. Paarlberg, Seitzinger and Lee (2007) studied the economic impact of regionalization of highly pathogenic AI outbreak in the U.S. They find that depending on the regionalization scenario, returns to capital in the poultry and egg sector would fall between \$602 and \$853 million over 16 quarters. Consumers of poultry meat were found to lose \$900 million in consumer surplus in the first four quarters.

In terms of international trade, a study by the Council for Agricultural Science and Technology (CAST 2006) shows that the U.S was the world's largest exporter of

broiler before the 2004 outbreaks (Delaware, New Jersey, Maryland and Texas in February 2004)³. The U.S exports were about 2,300 million tons in 2003 followed by Brazil with 1,550 million tons. After the 2004 outbreaks, the U.S export fell to 2,170 million tons behind Brazil who increased exports to about 2,416 million tons. Since then, the Brazilians have been the world's largest broiler exporters. As of 2009, U.S exports are about 2,744 million tons with Brazils at 3,306 million tons.

The economic impacts of foot-and-mouth disease (FMD) and bovine spongiform encephalopathy (BSE) outbreaks have also been significant (Jin, Mccarl and Elbakidze, forthcoming). Blancou and Pearson (2003) reported that the 1997 Taiwanese FMD outbreak cost the pork industry about \$15 billion. The National Audit Office (NAO 2002) reported that the UK government spent roughly \$2.6 billion in controlling and eradicating the 2001 FMD outbreak. Leeming and Turner (2004) reported that immediately after the announcement of the human infections associated with the 1996 BSE outbreak, beef product sales decreased by 40% and household consumption dropped by 26%.

The study of the Japanese' outbreak showed that wild birds are in fact natural carriers of the disease even though they do not show any pathologic signs. International movements of poultry products and people are the probable source of the Japanese and the Korean outbreaks (Nishiguchi et al., 2005). This shows that the threat of an outbreak is always present and international coordination is needed for an effective control of the disease. In their guidelines, the World Animal Health Organization (OIE), the World

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³ The Center of Disease Control (CDC) 2009 at http://www.cdc.gov/flu/avian/outbreaks/past.htm

Health Organization (WHO) and the USDA are collaborating to mitigate the probable future impact of the disease spread on the economy as well as on the human health. To achieve improvements in economic efficiency of the mitigation of an AI outbreak, a cost effectiveness analysis is needed.

2.2 Methodology and Typology of Models in Animal Disease Study

Generally, the economic questions raised by an animal disease outbreak modeling include one or more of the following issues.

- Costs to producers,
- Public agency costs of alternative mitigation strategies,
- Effects on prices and resultant implications for welfare and international trade,
- Consumers' reaction to outbreaks,
- National welfare changes,
- Inter-industry impacts,
- Employment implications in the livestock industry and
- Human health implications.

To answer these questions, several approaches have been developed in the

literature⁴. Here, some of the major approaches have been reviewed below.

Risk modeling is often used to estimate farms' cost or profit distribution as function of the probability of occurrence of an outbreak. Available risk modeling studies

 4 An excellent review of animal disease outbreak issues and methods for an economic cost assessment of the impact are discussed in Rich, Miller and Winter-Nelson (2005).

have used indicators such as the net present value (NPV), the benefit cost ratio (BCR), and the internal rate of return (IRR) to study whether preventive animal disease investments are worth making. Examples are found in Romero and Rehman (1989) and Meuwissen et al*.* (1999). Researchers using risk modeling frameworks have mainly addressed farm level impacts without examining the impact on other agents such as upstream industries and consumers.

Mathematical programming techniques optimizing some objective function (e.g. minimizing total cost of an outbreak, or maximizing total profit) have also appeared in the literature. Examples include the papers by Carpenter et al. (2007) and Elbakidze (2008). However, the need of information on data sometimes difficult to obtain and the complexity of mathematical modeling itself have limited its use in the animal disease outbreak analysis. These mathematical programming approaches also have possibilities of accounting for risk.

Partial equilibrium single-sector or multi-market analysis complements mathematical programming techniques when market supply and demand functions can be properly estimated. Partial equilibrium⁵ models are useful for in assessing the total welfare effects on affected markets. The aggregate welfare changes induced by the outbreak on producers, consumers and the upstream industries can be calculated using market supply and demand curves. In particular, price endogenous mathematical programming can solve endogenously for prices. This allows for a more realistic

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⁵ A theoretical treatment of welfare assessments in partial equilibrium framework is discussed in Just, Hueth and Schmitz (2004).

representation of the market dynamics during an outbreak. Studies by Paarlberg, Seitzinger and Lee (2002), Schoenbaum and Disney (2003) and Rich and Winter-Nelson (2007) have illustrated the application of these approaches.

Other popular methods are input-output models (Miller and Blair 1985) and computable general equilibrium models (Shoven and Whalley, 1992) that operate in social accounting framework. These models focus on inter-industry or inter-sector impacts. However, they are expensive to build and are beyond the scope of this study. Further they do not often have the detail needed to address issues in the animal disease setting. Among others, an example of animal disease impact assessment using Inputoutput methods is the study by Ekboir (1999). Regarding computable general equilibrium models, an example is Perry et al*.* (2003) could be mentioned.

In the next sections, a modeling framework combining mathematical programming and partial equilibrium market analysis will be presented. This model will be used in the next chapters for the economic cost assessment under two alternative AI outbreak mitigation strategies. Specifically, economic implications of using or not using vaccination in a hypothetical AI outbreak are modeled. Once the partial equilibrium model is developed, an epidemic model will be formulated to simulate the spread of AI. The resulting integrated dynamic epidemic-economic model includes simultaneously biological spread, economic consequences and possible mitigation strategies. Also, the integrated model is used to study an ex-ante vaccines production investment under uncertainty (Elbakidze and McCarl, 2006).

2.3 Economic Partial Equilibrium Model Formulation

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A partial equilibrium model which estimates changes in producers' and consumers' surplus resulting from an AI outbreak can be established following standard textbook expositions (Mas-Colell, Whinston and Jerry, 1995; Deaton and Muellbauer, 2006; Tirole, 2003). Historical market equilibrium prices and quantities are assumed to be observed in the *m* markets being analyzed. Using information on prices and quantities, the supply and demand curves for these commodities can be estimated, and the welfare calculated as the sum of the consumers' surplus (CS) and producers' surplus (PS) over the entire discrete outbreak period [1, T]. The consumers are assumed to have weakly separable preferences for poultry products and minimize their total expenditure⁶ $e(u, p) = Min{p'x : u(x) \ge u}$ with the corresponding indirect utility function being $\psi(e, p)$.

u is a direct utility function which is quasi-concave in its arguments and *p* is a vector of market prices. x is a vector of quantities and e is the expenditure on these commodities. Using Roy's identity, the marshallian demand functions are derived as $x_{kt}^d(p, e_t)$ $x_{kt}^d(p, e_t)$ and the corresponding inverse demand functions are $p_{kt}^d(x_{kt}^d, p_{jt}, e_t)$ *kt* p_{kt}^d (x_{kt}^d , p_{jt} , e_t). *k* and *t* are respectively commodity and time indexes. p_{it} is the vector of substitute and complement prices (other prices).

[.] ⁶ Weak separability assumption is a very important econometric device allowing estimation of a demand system only over a group of commodities. Also, expenditure can be used instead of income, as individual incomes are rarely observed in practice. A discussion of weak and strong separability can be found in Deaton and Muellbauer (2006).

Similarly, producers are assumed to maximize their profit

 $\phi(w, p_{kt}) = Max\{p_{kt}f(z) - w'z\}$, where *w* is a vector of input prices, p_{kt} is the market price of commodity k and ζ is the vector of input quantities used in production. By Hotelling's lemma, the supply functions are given as $x_{kt}^s(w, p_{kt})$ $x_{kt}^s(w, p_{kt})$ and the corresponding inverse supply functions are $p_{kt}^s(x_{kt}^s, w)$ *kt* $\int_{kt}^{s}(x_{kt}^{s},w)$.

The partial equilibrium welfare measure could be calculated by solving the following mathematical program for each outbreak sub-region:

(1)
$$
\Omega = \underset{x_{ki}^d, x_{ki}^i}{\text{Max}} \sum_{t=1}^T \sum_{k=1}^m \int_0^{x_{ki}^d} p_{ki}^d(x_{ki}^d, p_{ji}, e) dx_{ki}^d - \sum_{t=1}^T \sum_{k=1}^m \int_0^{x_{ki}^s} p_{ki}^s(x_{ki}^s, w_{ki}) dx_{ki}^s
$$

Subject to:

(2)
$$
x_{kt}^d - x_{kt}^s \le 0
$$
, For all $k = 1...m$ and $t = 1...T$
(3) $x_{kt}^d, x_{kt}^s \ge 0$, For all $k = 1...m$ and $t = 1...T$.

This maximization problem is motivated by the fact that outbreaks impact both supply and demand conditions for poultry products. The objective of the decision maker is to implement mitigation strategies that yield maximum economic welfare or minimize the potential losses for consumers and producers. Changes in the formulated welfare function due to the outbreak represent a measure of an economic cost on consumers and producers.

The RHS of equation (1) is the total welfare measured as the sum of consumers' and producers' surpluses. The first term on the RHS represents the sum of the areas underneath the demand curves of all the *k* commodities over the outbreak period [1, T].

The second term represents the areas underneath the supply curves of all the *k* commodities over the outbreak period. Ω is the total welfare value.

Equation (2) indicates that demand must be less than or equal to supply in all the *k* markets for all the*T* periods. Note that following Takayama and Judge (1971) the shadow prices of these constraints at the optimum are equivalent to the competitive market equilibrium prices of all the *k* commodities for the *T* periods.

Equation (3) represents the non negativity constraints of all the quantities at any period*t* .

This welfare function can be evaluated at the average data points of the variables *w*and *e* which become exogenous parameters in the solution of the model, since the integration is over quantities only. Variables x_{kt}^d and x_{kt}^s are choice variables in this problem.

This approach is a price endogenous model formulation and is widely used in applied economic analysis. Further discussion can be found in McCarl and Spreen (1980). By incorporating the supply shocks resulting from an outbreak from an epidemic model to this formulation, the changes in the welfare can be measured.

2.4 Epidemic Model

The AI epidemic analysis is based on the Susceptible Latent Infected and Removed (SLIR) approach (Durand and Mahul 2000; Schoenbaum and Disney 2003; Bates, Thurmond and Carpenter 2003; Elbakidze 2008, Ward 2007). At each time period, individual flocks are assumed to be in one of the four states of the disease progression. Those states are Susceptible (S) , Latent Infectious (L) , Symptomatic Infectious (I) and

Removed (R) . A flock that becomes infected flows through the four states as illustrated by the figure 2.1 below.

Given that the spread of the disease is being modeled in *k* flocks of different species at each time period *t*; let $S_k(t)$ be the number of susceptible flocks, $L_k(t)$ be the number of latent infectious flocks, $I_k(t)$ be the number of infected infectious flocks and $R_k(t)$ be the number of flocks removed from the population. At each period *t* of an outbreak, the sum of the susceptible flocks, latent flocks, infected flocks and removed flocks gives the total flocks in the outbreak sub-region as in the following identity.

(4)
$$
S_k(t) + L_k(t) + I_k(t) + R_k(t) = N_k, \forall k = 1...m.
$$

where, N_k is the total population of flocks of type k . Alternatively, identity (4) can be rewritten in terms of the proportion of flocks in each disease state by dividing all the identity by N_k . The identity becomes.

(5)
$$
s_k(t) + l_k(t) + i_k(t) + r_k(t) = 1, \forall k = 1...m.
$$

This form of the identity will be useful in terms of the optimization model and it is easier to interpret because all the variables are scaled down to a number in the interval

(0, 1). $s_k = S_k / N_k$, $l_k = L_k / N_k$, $i_k = I_k / N_k$ and $r_k = R_k / N_k$ are respectively the proportion of susceptible, latent, infected and removed flocks of type *k* .

Following Rushton and Mautner (1955) suppose that the variation of susceptible flocks over time depends only on their contacts with the infectious (symptomatic and latent) flocks. If b_{kj} is the probability of effective contacts sufficient to spread the disease from symptomatic infectious flocks of type *k* to susceptible flocks of type *j* , and d_{kj} is the probability of effective contacts sufficient to spread the disease from latent asymptomatic flocks of type *k* to a susceptible flock of type *j* , changes in the proportion of susceptible flocks over time following the differential equation below.

(6)
$$
\frac{ds_k(t)}{dt} = -s_k(t) \sum_{j=1}^m [b_{kj} i_j(t) + d_{kj} l_j(t)], \forall k = 1...m.
$$

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Equation (6) indicates that at each period t the proportion of susceptible flocks of type *k* decreases by the number of new infections generated by latent infectious and symptomatic infectious flocks of their own type and of other types *j* that they might be in contact with⁷. In other words, the spread of the disease comes from contacts of susceptible flocks with latent flocks and infected flocks.

Alternatively if vaccines are utilized during the outbreak period, the vaccinated flocks are immune and are therefore subtracted out each period *t* from the susceptible flocks because they are not vulnerable to the disease anymore. This implies that

⁷ This is a very general SLIR model where inter-flocks contact infections of heterogeneous flocks are modeled. A simple case where only intra flocks' contacts are considered is given in Ward (2007).

vaccinated flocks would not need to go through the latent and the infected states. This is illustrated in the figure below.

Figure 2.2 The vaccination effect on the model

If the proportion of vaccinated flocks V_k / N_k is $v_k(t)$, then the identity (5) becomes the following.

(7)
$$
s_k(t) + l_k(t) + i_k(t) + r_k(t) + v_k(t) = 1, \ \forall k = 1...m.
$$

Equation (6) must be rewritten to account for the reduction in susceptible flocks due to vaccination. The differential equation that accounts for the reduction of the susceptible flocks due to the vaccination is given below.

(8)
$$
\frac{ds_k(t)}{dt} = -s_k(t) \sum_{j=1}^m [b_{kj} i_j(t) + d_{kj} l_j(t)] - v_k(t), \ \forall k = 1...m.
$$

If it takes π periods for latent infectious flocks to become symptomatic (show the first clinical signs), changes in the latent flocks can be calculated as follows.

(9)
$$
\frac{dl_k(t)}{dt} = s_k(t) \sum_{j=1}^m [b_{kj}i_j(t) + d_{kj}l_j(t)] - s_k(t - \pi) \sum_{j=1}^m [b_{kj}i_j(t - \pi) + d_{kj}l_j(t - \pi)]
$$

$$
\forall k = 1...m.
$$

This equation (9) indicates that changes in the proportion of latent flocks equal the proportion of new infections generated by latent and symptomatic flocks at period *t* minus the proportion of infections generated π periods ago.

If it takes *h* periods for a symptomatic flock to remain in the system after showing the first signs of the disease then, changes in the number of infected flocks over time are described by the following differential equation.

(10)
$$
\frac{di_k(t)}{dt} = s_k(t-\pi)\sum_{j=1}^m [b_{kj}i_j(t-\pi)+d_{kj}l_j(t-\pi)] - s_k(t-\pi-h)\sum_{j=1}^m [b_{kj}i_j(t-\pi-h)+d_{kj}l_j(t-\pi-h)]
$$

$$
\forall k = 1...m.
$$

Equation (10) indicates that changes in the proportion of symptomatic flocks equal the proportion of flocks that were latent π periods ago and now are symptomatic minus the proportion of flocks that became symptomatic $(\pi + h)$ periods ago and are now leaving the symptomatic category. The second part of the RHS of equation (10) represents flocks that are removed. The removed flocks can be calculated using equation (11) below.

(11)
$$
\frac{d\mathbf{n}(t)}{dt} = s_k(t - \pi - h) \sum_{j=1}^m [b_{kj}i_j(t - \pi - h) + d_{kj}l_j(t - \pi - h)], \forall k = 1...m.
$$

This category normally consists of flocks that are dead due to the disease or human disease control.

Finally taking the derivative of identity (7) and solving for changes in the number of vaccinated flocks⁸ over time yields the following differential equation.

(12)
$$
\frac{dv_k(t)}{dt} = v_k(t), \forall k = 1...m.
$$

\n
$$
\frac{ds}{dt} + \frac{dl}{dt} + \frac{di}{dt} + \frac{dr}{dt} + \frac{dv}{dt} = 0 \Rightarrow \frac{dv}{dt} = -(\frac{ds}{dt} + \frac{dl}{dt} + \frac{di}{dt} + \frac{dr}{dt}) = v_k(t)
$$

Equations (8) to (12) represent the system of differential equations defining the epidemic model as follows.

$$
\begin{cases}\n\frac{ds_k(t)}{dt} = -s_k(t) \sum_{j=1}^m [b_{kj}i_j(t) + d_{kj}l_j(t)] - v_k(t) \\
\frac{d l_k(t)}{dt} = s_k(t) \sum_{j=1}^m [b_{kj}i_j(t) + d_{kj}l_j(t)] - s_k(t-\pi) \sum_{j=1}^m [b_{kj}i_j(t-\pi) + d_{kj}l_j(t-\pi)] \\
\frac{d i_k(t)}{dt} = s_k(t-\pi) \sum_{j=1}^m [b_{kj}i_j(t-\pi) + d_{kj}l_j(t-\pi)] - s_k(t-\pi-h) \sum_{j=1}^m [b_{kj}i_j(t-\pi-h) + d_{kj}l_j(t-\pi-h)] \\
\frac{d r_k}{dt} = s_k(t-\pi-h) \sum_{j=1}^m [b_{kj}i(t-\pi-h) + d_{kj}l(t-\pi-h)] \\
\frac{d v_k(t)}{dt} = v_k(t)\n\end{cases}
$$

The above epidemic model can be solved numerically if the initial states of the model $s_k(1)$, $l_k(1)$, $i_k(1)$, $r_k(1)$, $v_k(1)$ and the probability of disease transmission b_{kj} and d_{kj} are known. The latency period π and the symptomatic period *h* must also be defined to solve this system. The numerical solution will require the use of difference equations (the discrete time counterpart of the differential equations) instead of the continuous time equations defined in (13). Mathematically, for a small time interval, discrete models can be used as an approximate for continuous models (Judd 1998, ch.12).

Model (13) can also be used to account for randomness of the probabilities of disease transmission b_{kjq} and d_{kjq} . This approach is explored in section 4 of this dissertation. Other stochastic modeling taking time periods of transition to various states as random has been analyzed by Schoenbaum and Disney (2003) and Garner and Lack (1995). Once stochasticity is introduced, the distribution of the key output variables

involved in the model can be obtained using Monte Carlo simulation. The epidemic and the economic models thus defined can be linked to formulate the integrated model described below.

2.5 Integrated Epidemic-Economic Model

Here the integrated model combining the economic and the epidemic model is introduced to study the impact of simulated AI outbreak shocks on the poultry industry and households. The key assumption is that the outbreak produces a supply shock that reduces the market supply (Lloyd et al. 2006). Three main elements can affect the size of the supply shock during the outbreak. Namely, the rate of spread of the disease, the mitigation methods adopted, and the spatial characteristics of the affected sub-region. For instance supply would be reduced under:

- a fast moving disease affecting many flocks,
- a strategy where all infected flocks within the affected zone are depopulated and movements are restricted (currently the USDA recommended outbreak control strategy),
- a densely occupied region where many flocks are in near proximity to the outbreak.

 According to the LPAI (Low pathogenic Avian Influenza) Surveillance Standards in Texas (May, 2006), the currently recommended strategy for mitigating an AI outbreak would work as follows. Create within the disease sub-region three distinct zones with varying surveillance standards in an attempt to eradicate the disease in a maximum of one month. The first zone is called the affected zone and is roughly 5 miles (8 km) in radius surrounding the infected flocks where all birds in that zone are quickly depopulated. The second zone is the surveillance zone and is about 10 miles (16 km) in radius including the affected zone. In this second zone, intensive surveillance plus movement restrictions and AI testing will be enforced through the entire mitigation period. The third zone is called the buffer zone and is about 31 miles (50 km) in radius including the two previous zones. The combination of this strategy with particular regional characteristics (i.e. density of flocks) and whether the disease spreads beyond this containment will determine the impact of the disease on the market supply during the outbreak period.

Figure 2.3 below obtained from Pelzel, McCluskey and Scott (2006) portrays the zoning strategy actually implemented during the Gonzalez County (East of San Antonio) outbreak in 2004.

Figure 2.3 Map of zones initiated around the index farm in Gonzales, Texas

To be complete, we must address the question of how to handle any demand shifts in the welfare changes estimation. Demand for poultry products can decrease because consumers become suspicious of all poultry products and would prefer buying substitute products such as beef, pork and lamb. This effect is aggravated by the zoonotic nature of the AI disease. For instance Leeming and Turner (2004) found that the BSE outbreak in the UK depressed beef prices and increased lamb prices. Beach et al. (2008) conducted a study of AI outbreak in Italy and found that the outbreak reduced domestic demand for fresh poultry by 22%. An outbreak in the U.S might cause smaller or larger demand shock. Using the Italian case as a benchmark, scenarios of 10%, 20% and 30% U.S demand shocks will be analyzed in the next empirical sections of this dissertation. Figure 2.4 below describes welfare changes induced by supply shock only (Δ) and both supply and demand shocks together ($\Delta + A$). These two cases will be extensively studied in the next two empirical sections.

Figure 2.4 Welfare changes after supply and demand shifts

Finally, our integrated model can be written as the maximization of the following

mathematical program for any given outbreak sub-region.

(14)
$$
Max \Omega = \sum_{t=1}^{T} \sum_{k=1}^{m} \int_{0}^{x_{kt}^{d}} p_{kt}^{d} [x_{kt}^{d}, p_{jt}, e] dx_{kt}^{d} - \sum_{t=1}^{T} \sum_{k=1}^{m} \int_{0}^{x_{kt}^{s}} p_{kt}^{s} [(x_{kt}^{s} - \delta_{k} * N_{k} * (r_{kt} + c_{kt}), w_{kt}] dx_{kt}^{s} - \alpha_{1} \sum_{t=1}^{T} \sum_{k=1}^{m} F_{k} \varepsilon_{k} N_{k} s_{kt} - \sum_{t=1}^{T} \sum_{k=1}^{m} \alpha_{2k} N_{k} r_{kt} - \alpha_{3} \sum_{t=1}^{T} \sum_{k=1}^{m} N_{k} v_{kt}
$$
\nSubject to:

(15)
$$
S_{kt+1} - S_{kt} + S_{kt} \sum_{j=1}^{m} (b_{kj} i_{jt} + d_{kj} l_{jt}) \Delta t + v_{kt} \Delta t = 0 \forall k, t
$$

(16)
$$
l_{k+1} - l_{k} - s_{k} \sum_{j=1}^{m} (b_{kj} i_{jt} + d_{kj} l_{jt}) \Delta t + s_{k-\pi} \sum_{j=1}^{m} (b_{kj} i_{jt-\pi} + d_{kj} l_{jt-\pi}) \Delta t = 0 \forall k, t
$$

$$
(17) \quad i_{k+1}-i_{k} - s_{k-1} \sum_{j=1}^{m} (b_{kj}i_{j-\pi} + d_{kj}l_{j-\pi})\Delta t + s_{k-\pi-h} \sum_{j=1}^{m} (b_{kj}i_{j-\pi-h} + d_{kj}l_{j-\pi-h})\Delta t \qquad \qquad = 0 \,\forall k, t
$$

(18)
$$
r_{k+1} - r_{k} - s_{k-\pi-h} \sum_{j=1}^{m} (b_{kj} i_{j-\pi-h} + d_{kj} l_{j-\pi-h}) \Delta t = 0 \forall k, t
$$

$$
(19) \qquad v_{kt+1} - v_{kt} - v_{kt} \Delta t \qquad \qquad = 0 \,\forall k, t
$$

(20)
$$
x_{kt}^d - [x_{kt}^s - \delta_k N_k (r_{kt} + c_{kt})]
$$
 $\leq 0 \forall k, t$

$$
(21) \t c_{kt} - \theta_k \gamma_k s_{kt} = 0 \forall k, t
$$

$$
\begin{array}{ll}\n\text{(22)} & \pi - 5/F_k & = 0 \,\forall k \\
\text{(23)} & \frac{d}{dx} \text{ s} & \text{I} & \text{I} & \text{I}\n\end{array}
$$

(23)
$$
x_{kt}^d, x_{kt}^s, s_{kt}, l_{kt}, i_{kt}, r_{kt}, F_k, v_{kt}, c_{kt}
$$

\n $\ge 0 \ \forall k, t$
\n $\ge 1 \ \forall k$

$$
F_k \qquad \qquad \geq 1 \; \forall k
$$

The objective function of this maximization program is given in equation (14) and includes five terms. The first two terms represent the demand and supply terms as discussed in the economic model formulation. The negative supply shocks induced by removed flocks (r_{kt}) plus quarantined flocks (c_{kt}) are accounted for in the supply functions. The expression of the supply shock at any given period is $\delta_k N_k * (r_k + c_k)$. In this expression δ_k is the yield of poultry product k and N_k is the size of the flock. The

third term is the surveillance cost which depends on the testing frequency F_k and the proportion of birds submitted to the test $\varepsilon_k N_k s_{kt}$. The parameter ε_k is the proportion of birds tested during each period *t* of the outbreak (The exact number of birds to be tested is defined in the "manual of standard operating procedures for Texas LPAI response", May 2006). α_1 is the testing unit cost taken to be identical over flock types. The fourth term is the carcass disposal costs calculated as the cost of disposing all dead flocks $N_k r_{kt}$ with α_{2k} being the cost of disposing the dead flock of type *k*. The fifth expression is the vaccination costs. α_3 is the unit cost of vaccinating one bird and $N_k v_{kt}$ is the number of flocks vaccinated. Changes in this welfare function relative to its base of no outbreak represent the estimate of the total cost of the AI outbreak.

Constraints (15) , (16) , (17) , (18) and (19) are the five main equations of the epidemic model except that discrete time model is being used instead of continuous time model.

Constraint (20) contains the economic market equilibrium conditions modified to include the supply shocks resulting from depopulation and movement restrictions. ∆*t* is an interval of time period which is daily in this model.

The constraint (21) reduces access to market for flocks under quarantine. θ_k is a vector of disease control parameter. The construction of the movement restriction function will be discussed further below.

The constraint (22) accounts for early detection as influenced by surveillance. That is, as the surveillance becomes intense during the outbreak period, the likelihood of earlier detection increases and this will decrease the rate of the disease spread to other premises. The construction of the early detection function is discussed further below as well.

Constraints (23) and (24) are respectively non negativity constraints and a lower bound restriction constraint on the surveillance intensity (in order to avoid zero denominator problems).

This integrated model contains both epidemic and economic state and choice variables. The epidemic state variables are s_{kt} , l_{kt} , i_{kt} and r_{kt} and the choice variables are c_{kt} , F_{kt} and θ_k for all *k* and *t*. The latency period π is exogenous. Since the surveillance intensity and the latency period are linked, a sensitivity analysis on the values taken by π is necessary to determine the optimal surveillance intensity. The economic choice variables are the supply and the demand quantities of all the market commodities for every*t* .

The other parameters are exogenous to the model and have to be calculated. Those parameters are the unit cost of surveillance α_1 , the unit costs of carcass disposal α_{2k} , the unit cost of vaccination α_3 , and the proportions of susceptible flocks under surveillance ε_k . The epidemic parameters b_{kj} and d_{kj} which are the probabilities of disease transmission have to be calculated through survey data. Finally, the densities of flocks of each type in each region γ_k are to be calculated as the number of flock of type *k* in each sub-regions divided by the area of the region in squared miles. The initial flock populations N_k have to be obtained from secondary sources.
The number of flocks affected by the movement restriction is a function of the density of flocks γ_k and the number of susceptible flocks located in the disease area. Therefore, the expression can be written as c_{kt} (s_{kt} , γ_k) which is an increasing function of its arguments. Sub-regions that have more susceptible flocks per squared mile are likely to have more flocks restricted to market during the outbreak period. Postulating a multiplicative relationship, the explicit function can be expressed as $c_{kt}(\gamma_k, s_{kt}) = \theta_k \gamma_k s_{kt}$, for all *k*, and *t*. The parameter θ_k is endogenous and is between 0 and 1. It accounts for the fact that flocks types of higher density in the outbreak sub-region will imply more restricted flock movements. The proportion of restricted flocks is $\theta_k \gamma_k$. The choice of θ_k is critical because it gives the optimal proportion of flocks to be restricted in any region during the outbreak. If θ_k is near 0, then the number of flocks of type k to be restricted in the subregion is smaller than $\gamma_k s_k$, and if θ_k is near 1 then the proportion has to be about $\gamma_k s_k$.

2.5.2 Early Detection Constraint Formulation

The surveillance initiated through repetitive sample testing during the outbreak will increase the speed of detection of the disease during the latency period. Therefore, faster detection will be translated into a reduction in the length of the latency period. The latency period is a function of the surveillance intensity F_k . That is, $\pi = f(F_k)$

with $\partial \pi / \partial F_k \leq 0$. The specified function is $\pi = \frac{5}{F_k}$ with $F_k \geq 1$.

The number 5 in the numerator is the average number of days of latency based on the OIE estimations. For example, a surveillance intensity of $F_k = 2$ implies one

surveillance testing of flock type *k* in the circumference around the affected zone during the one month mitigation period. Therefore, the latency period π will be reduced from 5 days to 2.5 days if the surveillance frequency doubles.

2.6 Market Supply and Demand Specification and Estimation

Here we define a general model of supply and demand for estimating the poultry (Egg, Chicken and Turkey) supply and demand parameters. The approach follows closely resembles the analysis of Bullock, Jeong and Garcia (2003). The demand functions in the three cases are specified as a function of own price, complement and substitute prices, and demand shifters as in the table 2.1 below.

Table 2.1 The General Structural Model

Chicken (*ch*) demand and supply for retail Demand: $x_{dt}^{ch} = x_{dt}^{ch}(p_t^{ch}, p_t^{eg}, p_t^{tk}, e_t, pop_t)$ *tk t eg t ch t ch dt* $x_{dt}^{ch} = x_{dt}^{ch}(p_t^{ch}, p_t^{eg}, p_t^{tk}, e_t, pop)$ Supply: $x_{st}^{ch} = x_{st}^{ch} (p_t^{ch}, w_t, \text{rates}_t)$ *ch t ch st* $x_{st}^{ch} = x_{st}^{ch}$ (p_t^{ch} , w_t , rates Market clearing $x_{dt}^{ch} = x_{st}^{ch}$ $x_{dt}^{ch} = x$ Eggs (eg) demand and supply for retail Demand: $x_{dt}^{eg} = x_{dt}^{eg} (p_t^{eg}, p_t^{ch}, p_t^{tk}, e_t, pop_t)$ *tk t ch t eg t eg dt* $x_{dt}^{eg} = x_{dt}^{eg} (p_t^{eg}, p_t^{ch}, p_t^{tk}, e_t, pop)$ Supply: $x_{st}^{eg} = x_{st}^{eg} (p_t^{eg}, w_t, rates_t)$ *eg t eg st* $x_{st}^{eg} = x_{st}^{eg}$ (p_t^{eg}, w_t , rates Market clearing $x_{dt}^{eg} = x_{dt}^{eg}$ $x_{dt}^{eg} = x$ Turkey (tk) demand and supply for retail Demand: $x_{dt}^{tk} = x_{dt}^{tk} (p_t^{tk}, p_t^{eg}, p_t^{ch}, e_t, pop_t)$ *ch t eg t tk t tk dt* $x_{dt}^{tk} = x_{dt}^{tk} (p_t^{tk}, p_t^{eg}, p_t^{ch}, e_t, pop)$ Supply: $x_{st}^{tk} = x_{t}^{tk} (p_{t}^{tk}, w_{t}^t, rate_{t})$ *tk t tk t* $x_{st}^{tk} = x_t^{tk}$ (p_t^{tk}, w_t , rates Market clearing $x_{dt}^{tk} = x_{dt}^{tk}$ $x_{dt}^{tk} = x$

Note: The notation is consistent with the economic model defined in the section 2.3 where pop_t and *rates*, are respectively the human population and the interest rates at time *t* .

Economic theory does not give any indication about which functional form one must specify in the econometric estimation. Several demand function specifications have been used in the economic literature⁹.

Elasticity estimations studies, usually employ the almost ideal demand system (AIDS) specification and estimate the reduced form parameters of the demand system. The AIDS specification uses a flexible functional form specification and has the advantage that it imposes theoretical restrictions such as adding up, homogeneity and symmetry on the demand system. Examples of empirical studies using AIDS specifications include Deaton and Muellbauer (1980), Golan, Perloff and Shen (2001).

Alternatively, some authors such as Alston and Chalfant (1993), Bryant and Davis (2001) use a Rotterdam model specification. The Rotterdam specification can impose all the above restrictions as well. Even though these specifications are appealing, they do not have explicit forms that are needed for this study. Other functional forms which are more explicit in quantity-price relation are the linear and the log-linear demand system. These specifications have been widely used in the demand estimation literature. Examples of studies using those models are Brester and Wohlgenant (1993) and Capps (1989) who used log linear demand specification. Also, Leeming and Turner (2004) used a log linear demand system to study the impact of the BSE (bovine spongiform encephalopathy) outbreak on prices in UK. This study will use log linear and linear specifications to estimate the demand and supply system coefficients because of their explicit price-quantity relationship.

 \overline{a}

⁹ A review of demand and supply analysis in agricultural economics is in Sadoulet and De Janvry (1995).

2.7 Pre-event versus Post-event Decision Making Model

AI outbreaks can involve one of several virus strains. Commercial vaccines are not always readily available for all the possible strains. Therefore, pre-outbreak preparation of vaccines production might be necessary for effective outbreak control. Following Elbakidze and McCarl (2006), the integrated model can be reformulated to analyze the critical outbreak probability level that will require an upfront investment in vaccines. The pre-event and post-event activities related to the occurrence or not of the outbreak can be analyzed as in the figure 2.5 below.

Figure 2.5 Event probability and decision making stages

 In the context of this integrated model, the pre-outbreak activity involves whether investment in vaccine production must be undertaken or not. Since the preoutbreak activity must be decided upon before an outbreak ever occurs it is irreversible and involves a sunk cost plus vaccines can be used for control only if they were made available before the outbreak. Following this logic, let *Y* be a binary decision variable

that takes $Y = 1$ if indeed investment in vaccines is made and $Y = 0$ if not. Let *FC* be the fixed cost incurred by the vaccine production and stocking. Thus, the modified version of the integrated model can be written as an expected welfare maximization problem. Below the objective function representing the total welfare function has been rewritten and the irreversibility constraint has been added to the existing set of constraints previously defined in the integrated model.

$$
Max\Omega = -FC*Y + P_e * \left(\frac{\sum_{t=1}^{T} \sum_{k=1}^{m} x_{kt}^{d}}{\sum_{t=1}^{d} x_{kt}^{d}} p_{kt}^{d} [x_{kt}^{d}, p_{jt}, e] dx_{kt}^{d} - \sum_{t=1}^{T} \sum_{k=1}^{m} \sum_{0}^{x_{kt}^{d}} p_{kt}^{s} [x_{kt}^{s} - \delta_k * N_k * (r_{kt} + c_{kt}), w_{kt}] dx_{kt}^{s}\right) \n+ (1-P_e) * \left(\sum_{t=1}^{T} \sum_{k=1}^{m} \sum_{0}^{x_{kt}^{d}} p_{kt}^{d} [x_{kt}^{d}, p_{jt}, e] dx_{kt}^{d} - \sum_{t=1}^{T} \sum_{k=1}^{m} \sum_{0}^{x_{kt}^{d}} p_{kt}^{s} [x_{kt}^{s}, w_{kt}] dx_{kt}^{s}\right)
$$

Subject to:

$$
(26) \quad -FC*Y + v_{kt} \le 0 \ \forall, k, t
$$

where, the three parts of this new expected objective function include the incurred fixed costs if vaccines are made $(-FC^*Y)$, the outbreak probability (P_e) times the welfare level in case of outbreak and $(1 - P_e)$ times the welfare level in case of no outbreak. Constraint (26) is the irreversibility constraint used to allow vaccination v_{kt} to be nonzero only when the *Y* variable for stocking the vaccine is 1, otherwise the number of vaccinated flocks is zero. That is, for any non zero vaccination activity to occur, the fixed cost must be incurred. Maximizing this expected welfare objective function under constraint (25) added to all other existing constraints of the integrated model, the critical

probability P_e above which upfront investment in vaccines is necessary can be determined.

2.8 Summary

A dynamic integrated economic-epidemic model that evaluates the cost effectiveness of avian influenza mitigation options is postulated. The economic model uses a price endogenous formulation so that a possible change of prices can be captured dynamically. The epidemic model is a susceptible, latent, infected and removal (SLIR) model. Disease mitigation strategies such as earlier detection, quarantine and movement restrictions and vaccination are introduced in the epidemic model formulation to control the disease spread. To link the economic and the epidemic model, supply shocks induced by quarantined and depopulated flocks are integrated into the economic model formulation. Finally, a decision making under uncertainty problem is formulated to determine the threshold outbreak probability above which ex-ante vaccine production could be undertaken.

3. EVALUATING THE COSTS OF AN AI OUTBREAK IN TEXAS: A DETERMINISTIC ANALYSIS APPROACH

This section uses the deterministic version of the integrated economic-epidemic model developed in the previous section to study the impact of a hypothetical outbreak. The impact is measured as the total welfare loss due to the outbreak as incurred by households and the national poultry industry. The total outbreak costs are estimated with and without vaccination as a control strategy and the outcomes of these two strategies are compared. The total welfare losses include the effects on producers, and consumers plus the cost of mitigation. Welfare losses to producers and to consumers are measured respectively as the changes in producers' and consumers' surpluses induced by the outbreak. The cost of mitigation corresponds to the amount spent on the control of the outbreak. This includes the surveillance cost, the carcass disposal cost and the vaccination cost. The analysis uses the procedures developed by Lloyd et al. (2006) to provide estimated price responses to the outbreak.

Since vaccines would be used to control the outbreak ex-post only if they have been produced ex-ante, this section uses the integrated model to determine the critical outbreak probability level above which an ex-ante investment in vaccines would be economically optimal. This critical outbreak probability level above which ex-ante investment is optimal has been calculated following a framework developed in Elbakidze and McCarl (2006).

The remainder of this section is organized as follows. . Section 1 presents a brief overview of Texas poultry farm case study used in this study. The economic and the

epidemic data used are presented in section 2. The econometric results of the demand and supply functions estimated for use in the study are given in section 3. The estimated outbreak costs are presented in Section 4 followed by the results on ex-ante vaccine investment in section 5. Section 6 concludes the section.

3.1 Brief Overview of Texas Poultry Operations

 \overline{a}

In the 2007 USDA poultry inventory¹⁰, Texas is divided into four main poultry subregions based on the number of birds produced. In order of poultry population, the four sub-regions are District 8-N (7,087,000 birds), District 5-N (5,300,000 birds), district 5- S (867,000 birds) and rest of the state which is composed of less dense districts including the District 1-N High Plains, District 1-S High Plains, District 2-N Low Plains, District 2-S Low Plains, District 3 Cross Timbers, District 4 Backlands, District 6 Trans-Pecos, District 7 Edwards Plateau, District 10-N South Texas, District 10-S Lower Valley, District 8-S Coastal Bend, District 9 Upper Coast. These last 12 less dense Districts have a total of 5,291,000 birds. The total number of birds in Texas totals to 18,545,000. This study will focus only on the first three of the four sub-regions (District 8-N, District 5-N and District 5-S), the last sub-region includes Districts that are less dense and far away from each other making it difficult to analyze in the context of the epidemic disease spread model used in this study.

Based on the US Agriculture Census of 2002, poultry farms in each district can be categorized into five types of farms as follows.

¹⁰http://www.nass.usda.gov/Statistics_by_State/Texas/Publications/County_Estimates/CE_maps/CE_poul. htm

- large size layers operations of more than 100,000 birds (Layersl),
- small size layers operations between 400 birds to 100,000 birds (Layerss),
- broiler operations (Broiler),
- turkey operations (Turkey) and
- Backyard operations of layers less than 400 birds (Backyard).

The total number of flocks in each of these three relevant sub-regions is given in the table1 below. Here a flock is defined as the number of premises of same farm type as given above. This is shown in the table 3.1 below.

		-			
	Laversl	Laverss	Broiler	Turkey	Backyard
1. District 8-N	10	54	395	235	1526
2. District 5-N		95	663	127	998
3. District 5-S		16	260	155	849
4. Other Districts		22	1162	1072	6331
Total Texas	23	187	2480	1589	9705

Table 3.1 Number of Farms per Sub-region

Source: Calculated from US Agricultural Census 2002 Data

The density of flocks in each sub-region calculated as the ratio of the number of farms to the area in squared miles of the sub-region is given in table 3.2 below.

Source: Calculated from US Agricultural Census 2002

The tables show that backyard farms are the most prevalent types of flocks in each of the three sub-regions. This situation is of specific concern because backyard farms do not usually apply strict biosecurity measures. As a result, they are the most susceptible to the disease. Broiler farms have the second highest density.

3.2 Data for the Study

Two categories of data sets are used in the study. The first is the epidemic data which are contact rates between flocks. These data were calculated by surveying poultry producers. The second category is the production, consumption and price data used in the econometric estimation. Most of these data are obtained from the USDA-ERS database.

3.2.1 Epidemiologic Data

The epidemic data are the direct and the indirect daily contact rates. To estimate these contacts, a survey was conducted on Broiler, layers and turkey farms in collaboration with poultry science and veterinary school professors. The objective of the survey was to understand how the industry functions and to obtain necessary information to calculate the direct and the indirect contact rates. The survey instrument is given in the appendix. Direct contacts are calculated using the following information.

• Layers farms: Egg production begins when layers farms receive chicks from hatcheries (every 6 weeks). Then they feed them until they become adults and enter the egg production process. The chicks are the only live birds that enter the layer farms. These farms have also direct contact with other farms when receiving other types of eggs that are not produced in their premises and vice

versa (for instance a surveyed farm was found to receive brown eggs once every 4 weeks from another farm located in Dallas area).

- Broiler farms: Chicken process begins when farms receive chicks from hatcheries (every 4 weeks). These chicks are fed until their seventh week when they are sent to the factory for processing into meat.
- Turkey farms: their production process is more complex. The only direct contact occurs when birds are moved to another place. This happens five times a year.

Following Ward (2007) the average direct contact rate for each flock type can be

calculated as \sum *ⁱ days of contacts number of real contacts* (days of contacts) for each type of contact*i* using the above

information.

Direct average contact for layers farms: $1/42 + 1/28 = 0.06$ contact per day Direct average contact for broiler: $1/28 = 0.04$ contact per day Direct average contact for turkeys: $5/365=0.01$ contact per day Indirect contacts are calculated using the following information.

• Layer farms: there are multiple indirect contacts with other layer farms and these include feed trucks' movements, veterinarians and nutritionists' movements and others. Feed trucks come about 6 to 9 times a week to bring feed and vitamins into the farms. Other truck movements also occur such as propane tanks fill up (2/month), utility services (1/month), Electricity and plumbing (1/month), broken egg pick up (every 6 week), disable animal pick up (every 6 week), local volume

retailer (2/week), food distribution (1/month), eggs transport (9/week), and veterinarian visits (4-6 times a year).

- Broiler farms: indirect contacts for broiler farms are similar to those of layer farms. Feed trucks come about 25 times per 7 weeks, consulting veterinarians visit 5 times a year, electricity and plumbing workers come once a year, utility services come once a month and the propane tanks come once every seven week.
- Turkey farms: indirect contacts include truck movements, veterinarians and nutritionists' movements similar to the case of layers and Broiler. Feed trucks come once a week, the veterinarian come 3 times every 3 months, the nutritionist comes once a year, the propane trucks come 4 times a week and the loading crews come 4 times a week.

From the information above the indirect contacts are calculated as follows.

Indirect average contacts for layers' farms:

7.5/7+2/30+1/30+1/30+1/42+1/42+2/7+1/30+9/7+5/365=2.87 contacts per day

Indirect average contacts for broiler farms:

25/49+5/365+1/365+1/30+1/49=0.57 contacts per day

Indirect average contacts for turkeys' farms:

 $1/7+4/7+1/90+1/365+4/7=1.29$ contacts per day

Base on these calculations, the following matrix (table 3.3 below) is constructed to represent the number of average contacts as the sum of the direct and the indirect contacts on the diagonals and only the indirect contacts elsewhere.

	Layesl	Laverss	Broiler	Turkey	Backyard
Layersl (More than 100,000)	2.93	2.87	2.87	2.87	2.87
Layerss (400 to 100,000)	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	1.30	1.29
Backyards (less than 400)	2.87	2.87	2.87	2.87	2.93

Table 3.3 Infected Daily Contact Rates

Similarly, taking the latency contacts as equivalent to the direct contacts on the diagonals and the indirect contacts off-diagonals, the matrix of latency daily contacts is given in the table 3.4 below.

	Layes	Layerss	Broiler	Turkey	Backyard
Layersl (More than 100,000)	0.06	2.87	2.87	2.87	2.87
Layerss (400 to 100,000)	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
Backyards (less than 400)	2.87	2.87	2.87	2.87	0.06

Table 3.4 Latent Daily Contact Rates

The above daily contacts are used to calculate the probability of disease transmission also called the probability of effective contacts. Again, following Ward (2007), the probability of disease transmission equals the number of daily contacts divided by the population of flocks involved.

The infectious probability of disease transmission is calculated as *N* −1 *daily contacts* , where N is the total number of flocks involved in the contact. After calculation, these

probabilities of disease transmission are compiled in the table 3.5 and table 3.6 below for the three epidemic sub-regions.

Effective contacts rates (District 8-N)							
	Layersl	Layerss	Broiler	Turkey	Backyard		
Layersl	0.32555	0.04629	0.00712	0.01181	0.00187		
Layerss	0.04629	0.05528	0.00642	0.01000	0.00181		
Broiler	0.00141	0.00127	0.00154	0.00090	0.00029		
Turkey	0.00530	0.00449	0.00189	0.00555	0.00073		
Backyard	0.00187	0.00187	0.00149	0.00163	0.00192		
		Effective contacts rates (District 5-N)					
Layersl	0.97666	0.02958	0.00431	0.02224	0.00287		
Layerss	0.02958	0.03117	0.00379	0.01304	0.00263		
Broiler	0.00085	0.00075	0.00092	0.00072	0.00034		
Turkey	0.01000	0.00586	0.00151	0.01031	0.00114		
Backyard	0.00287	0.00263	0.00173	0.00255	0.00293		
		Effective contacts rates (District 5-S)					
Layersl	0.97666	0.15944	0.01095	0.01828	0.00337		
Layerss	0.15944	0.19533	0.01047	0.01698	0.00332		
Broiler	0.00217	0.00208	0.00235	0.00138	0.00051		
Turkey	0.00821	0.00763	0.00288	0.00844	0.00128		
Backyard	0.00337	0.00332	0.00259	0.00286	0.00345		

Table 3.5 Probability of Disease Transmission from Symptomatic Flocks

Table 5.0 I Tobability of Effective Colliact II olli Eatent Plocks Effective indirect contacts (District 8-N)							
	Layersl	Layerss	Broiler	Turkey	Backyard		
Layersl	0.00666	0.04629	0.00712	0.01181	0.00187		
Layerss	0.04629	0.00113	0.00642	0.01000	0.00181		
Broiler	0.00141	0.00127	0.00144	0.00090	0.00029		
Turkey	0.00530	0.00449	0.00189	$4.2E-05$	0.00073		
Backyard	0.00187	0.00181	0.00149	0.00163	3.9E-05		
		Effective indirect contacts (District 5-N)					
Layersl	0.02000	0.02958	0.00431	0.02224	0.00287		
Layerss	0.02958	0.00063	0.00379	0.01304	0.00263		
Broiler	0.00085	0.00075	0.00086	0.00072	0.00034		
Turkey	0.01000	0.00586	0.00151	7.9E-05	0.00114		
Backyard	0.00287	0.00263	0.00173	0.00255	6.0E-05		
		Effective indirect contacts (District 5-S)					
Layersl	0.02000	0.15944	0.01095	0.01828	0.00337		
Layerss	0.15944	0.00400	0.01047	0.01698	0.00332		
Broiler	0.00217	0.00208	0.00220	0.00138	0.00051		
Turkey	0.00821	0.00763	0.00288	$6.4E-05$	0.00128		
Backyard	0.00337	0.00332	0.00259	0.00286	7.0E-05		

Table 3.6 Probability of Effective Contact from Latent Flocks

These probabilities of disease transmission calculated here are similar to those calculated in the literature (e.g. in Carpenter et al., 2007 similar probabilities are given for cattle in California).

3.2.2 Economic Data

National monthly data from USDA-ERS covering the period of 1995 to 2003 or a total of 108 observations per variable were first collected. To match the market equilibrium with daily disease spread, daily frequency of market equilibrium data were estimated using cubic spline (Li and Racine, 2007) interpolation. SAS software has a program that is used to disaggregate the production (adjusted for imports and exports) and the consumption data from monthly frequency to daily frequency. The monthly average prices are also adjusted into daily averages. The supply and the demand system for three poultry products (Chicken, Eggs and Turkey) were estimated using these daily frequency data. Other independent variables used such as population and interest rates are taken respectively from the US Census Bureau and the Federal Reserve. The income variable is the total expenditure on poultry products. The estimated demands are at the retail level. The complete summary statistics describing the monthly and the daily frequency data is given in the table 3.7 below.

	Table 3.7 Summary Statistics of the Economic Data				
Variable			Daily Data		Monthly Data
	Egg Demand and Supply variables	Mean	Std. Dev.	Mean	Std. Dev.
cegg	Consumption (Million dozens of eggs)	15.675	1.066	477.085	35.208
prodegg	Production (Million of pounds)	15.612	0.992	475.168	33.039
ppeg	Price received by producers (Dollars)	0.663	0.093	0.663	0.090
peg	Retail prices (Dollars)	1.022	0.129	1.022	0.128
feedpegg	Feed price for eggs production (Dollars)	0.284	0.052	0.284	0.053
	Chicken Demand and Supply variables				
cch	Consumption (Million of pounds)	66.493	7.497	2023.736	228.591
prodch	Production (Million of pounds)	67.270	7.583	2047.394	230.201
ppch	Price received by producers (Dollars)	0.589	0.040	0.589	0.040
pch	Retail prices (Dollars)	1.545	0.060	1.545	0.060
feedpch	Feed price for chicken production(Dollars)	0.164	0.024	0.164	0.024
	Turkey Demand and supply variables				
ctkey	Consumption (Million of pounds)	13.447	3.836	409.288	107.109
prodtkey	Production (Million of pounds)	13.539	1.104	412.072	32.609
pptkey	Price received by producers (Dollars)	0.644	0.054	0.643	0.053
ptkey	Retail prices (Dollars)	1.041	0.052	1.041	0.050
feedptkey	Feed price for turkey (Dollars)	0.054	0.011	0.054	0.011
tkeydum	Thanksgiving month dummy	0.082	0.274	0.083	0.277
	Other independent variables				
expd	Expenditure on the poultry (Million of Dollars)	133.086	17.214	4050.753	530.913
rates	Interest Rates (percentage)	0.074	0.017	0.074	0.018
pop	Population (Million of people)	276.086	9.918	276.086	9.918
pbeef	Beef retail prices (Dollars)	2.769	0.278	2.769	0.279
ppork	Pork Retail prices (Dollars)	2.475	0.199	2.475	0.199

Table 3.7 Summary Statistics of the Economic Data

3.3 Demand and Supply System Estimation Results

Given that daily consumption, production quantities are approximated from monthly data to daily data; the estimation is subject to measurement error problems. According to Cameron and Trivedi (2006 pp.899-921), the measurement error on the dependent variables (consumption and production in this case) do not affect the consistency of the estimated coefficients although they may be less efficient (big variance of the estimated coefficients). In contrast, the measurement error on the independent variable (prices in this case) leads to correlation between that independent variable and the error term of the regression. This causes endogeneity in the model and produces biased and inconsistent estimates of the coefficients. To correct these problems instrumental variables (IV) such as pork prices and beef prices are used as suggested in Cameron and Trivedi (2006) and Wooldridge (2002).

 Demand and supply systems of these three poultry products (Chicken, Eggs and Turkey) are estimated simultaneously using three stage least square (3SLS) to improve the efficiency of the estimated coefficients. Symmetry is imposed on the cross price coefficients during the estimation. The results from the econometric estimation are presented in the table 3.8 below. These results are presented for both linear and loglinear demand and supply system specifications.

Table 3.8 Estimation Results

radic 9.0 Estimation results Models	Linear		Log-Linear	
Egg Demand (1)	Coef.	Z-stat	Coef.	Z-stat
pegg	-0.56781	-6.14	-0.07392	-12.22
pch	-9.75866	-53.99	-0.14397	-43.89
ptkey	-0.68738	-2.49	-0.09557	-5.66
expd	0.095322	124.01	0.51176	92.04
constant	19.35192	147.58	0.318428	11.7
χ^2 – Statistics		36279.88		12930.01
Egg Supply (2)				
pegg	16.83625	90.98	0.269137	33.56
feedpeg	-6.30533	-9.61	-0.26193	-53.19
constant			2.409064	378.92
χ^2 – Statistics		191657.40		3020.63
Chicken Demand(3)				
pch	-41.9218	-58.74	-1.06529	-58.66
pegg	-9.75866	-53.99	-0.14397	-43.89
ptkey	18.7085	17.93	0.309222	18.2
expd	0.519326	198.05	1.079478	161.35
constant	52.67307	99.25	-0.62722	-22.4
χ^2 – Statistics		44405.69		36492.72
Chicken Supply (4)				
prodch	57.50628	209.99	2.002151	58.29
feedpch	-83.7949	-33.95	-0.25065	-29
rates	-105.794	-30.42		
constant			2.877051	155.64
χ^2 – Statistics		632938.11		5598.27
Turkey Demand (5)				
ptkey	-46.5392	-26.18	-2.54547	-21.5
pegg	-0.68738	-2.49	-0.09557	-5.66
pch	18.7085	17.93	0.309222	18.2
expd	0.06917	16.67	0.899133	26.86
constant	24.47036	37.54	-1.85804	-11.33
χ^2 – Statistics		4052.25		1198.16
Turkey Supply(6)				
ptkey	13.15901	201.98	0.673761	17.53
feedptkey			-0.05157	-7.76
tkeydum	2.277807	39.52	0.13695	27.1
rates	-4.96886	-5.62		
constant			2.413095	122.4
χ^2 – Statistics		541781.22		812.67

Note: Variables are defined in table 3.7.

The signs of the estimated coefficients are consistent with economic theory predictions. In the demand equations, quantities are negatively related to prices and positively related to expenditures. In the supply equations, quantities are positively related to prices and negatively related to input prices.

In the Egg demand equation, chicken price and turkey price have negative coefficients that are statistically significant meaning that the two goods behave as substitutes for eggs. In the Chicken demand equation, turkey price has a positive and significant coefficient showing that chicken and turkey are complementary goods. Finally, in the Turkey equation the egg price coefficient is negative and significant meaning that the two goods are substitutes.

Holding exogenous variables in each demand equation at their mean, the inverse demand curves can be expressed as depending only on own quantities: The linear model specification becomes:

(27)
$$
\begin{bmatrix} pegg \\ pch \\ ptkey \end{bmatrix} = \begin{bmatrix} 28.607 \\ 3.132 \\ 1.330 \end{bmatrix} + \begin{bmatrix} -1.761 & 0 & 0 \\ 0 & -0.0239 & 0 \\ 0 & 0 & -0.0215 \end{bmatrix} \begin{bmatrix} cegg \\ cch \\ ctkey \end{bmatrix}.
$$

Similarly, fixing the exogenous variables of the supply equation at their mean yields the following linear inverse supply equations depending on own quantities:

(28)
$$
\begin{bmatrix} \text{peg} \\ \text{pch} \\ \text{ptkey} \end{bmatrix} = \begin{bmatrix} 0.107 \\ 0.376 \\ 0.014 \end{bmatrix} + \begin{bmatrix} 0.059 & 0 & 0 \\ 0 & 0.017 & 0 \\ 0 & 0 & 0.076 \end{bmatrix} \begin{bmatrix} \text{cegg} \\ \text{cch} \\ \text{ctkey} \end{bmatrix}.
$$

Based on the chi-squared statistics presented in the table 3.8 above, the linear specification is preferred to the log-linear model. For that reason only the linear specification will be used in the remainder of this work.

Investigation shows the estimated elasticities in this linear specification are comparable to the existing estimated elasticities in the literature. In particular eggs, chicken and turkey own price and expenditure elasticities calculated from our specification are similar to the elasticities found in the literature. Huang and Lin (2000) used AIDS specification and found that egg own price elasticity is -0.0569 and the expenditure elasticity is about 0.8039 and our linear specification found the own price elasticity to be -0.0364 and the expenditure elasticity to be 0.806. Alston and Chalfant (1993) used a Rotterdam model and found that the own price elasticity for chicken is - 0.94 and the expenditure elasticity is 1.06 and our model found the own price elasticity to be -0.97 and the expenditure elasticity to be 1.03. Hahn (2001) estimated the own price elasticity for turkey as -0.553 and our specification found the own price elasticity for turkey to be -3.58. Our estimated elasticity value for turkey is different from the literature because Hahn's model did not account for the seasonal consumption of turkey during the Thanksgiving period. Not accounting for thanksgiving in our model yields a result similar to Hahn (2001).

These demand and supply functions are used to calculate the total welfare changes induced by the AI outbreak.

3.4 Empirical Results of AI Cost Outbreak

Several sets of empirical results are now presented. First, the base results of the market equilibrium prior to the outbreak are given and are compared to the original data for consistency. Second, the epidemic model simulation results are compared to the existing literature. Finally, results of the integrated model are presented.

3.4.1 Base Welfare Level Prior to the Outbreak

Here the national market equilibrium and the calculated welfare values prior to the outbreak are presented using the linear demand and supply functions estimated above. The results are obtained by maximizing the sum of the welfare in the three poultry product markets over 30 days under market equilibrium constraints. The summary of the GAMS software maximization output is given in the table 3.9 below.

Market Equilibrium (daily)	Equilibrium quantities	Equilibrium Price
Eggs	15,659,000 (dozens)	1.031 (dollars)
Chicken	67,195,000 (pounds)	1.518 (dollars)
Turkey	13,567,000 (pounds)	1.045 (dollars)
Welfare (30 days)	Producer Surplus	Consumer Surplus (dollars)
Surpluses	1,578,220,000 (dollars)	8,160,799,000 (dollars)

Table 3.9 Market Equilibrium and Welfare Level before the AI Outbreak

These results are consistent with the market data used in the econometric estimation in the previous section. Equilibrium prices and quantities are in the range of the market data used in the estimation. The total welfare level prior to the outbreak is estimated as \$9,738,019,000 (This is a sum of welfare in a 30 day period). The producers' surplus prior to the outbreak is estimated as \$1,578,220,000 and the consumers' surplus is

 $$8,160,799,000¹¹$. Change in these surpluses induced by the simulated outbreak will be used when calculating the cost of the outbreak.

3.4.2 Epidemic Model Simulation

Here the epidemic model presented in section 2 is used to simulate an outbreak. The epidemic simulation is based on the following assumptions:

- The hypothetical outbreak starts in a backyard farm similar to the 2004 outbreak in Gonzales Texas and spreads through daily contacts.
- The outbreak is simulated in one Texas poultry sub-region of District 8-N and is assumed to spread only within that region.

Figure 3.1 District 8-N: simulated epidemic model of large layers

 \overline{a}

 11 Results of the log-linear specification are not consistent with the data and are not presented here for that reason.

These simulated epidemic curves in Figure 3-1 are consistent with several studies reported in the literature (e.g. Durand and Mahul, 2000; Ward, 2007). As the disease spreads, the proportion of latent infectious and infected symptomatic flocks rises to a maximum on the $8th$ day and starts dropping thereafter. At the same moment, the proportion of dead or removed flocks increase and the proportion of susceptible flocks decrease until all the infected or removed flocks are dead. Similar epidemic curves are obtained using the three other sub-regions contact rates data but are not presented here.

3.4.3. Empirical Results of the Integrated Epidemic-economic Model

In the following, the outbreak cost is estimated based on the 30 days simulated outbreak. This outbreak is simulated using Texas poultry industry data but the impact is measured at the national scale. The results obtained here are based on the following assumptions:

- Only some proportion of the susceptible flocks is under surveillance and the surveillance cost depends only on the number of birds tested for the disease. Consistently with Texas AI response document (2006), 20 birds are tested in every farm. Dividing the 20 bird sample by the total birds in a flock gives the proportion under surveillance. The unit cost of testing is estimated as \$15 per bird and is obtained from farmers during the survey.
- Yields of eggs, chicken and turkey meat used in the model are drawn from McCarl Forestry and Agriculture Sector Optimization Model (FASOM) data.
- The cost of carcass disposal is taken as the digging and the burial costs of the removed or depopulated flocks. These costs are obtained from farmers during the survey and are estimated respectively as \$8,000 for large layer farms, \$6,000 for

small layers and broiler farms, \$4,000 for turkey farms, and \$1000 for backyard farms.

- The outbreak starts in one backyard flock and spreads through contacts to other farms. In the simulation, the disease starts with one latent flock and spreads from there to the other flocks.
- Vaccination unit costs are estimated using information obtained from the literature, the survey, and AI vaccine manufacturers. Based on the Food and Agriculture Organization (FAO) report on the AI disease control in Vietnam (Smith, 2007), vaccine production cost is about 1.2 cents/dose. The Center for Infectious Disease Research and Policy (CIDRAP, 2005) reported on their website that an Iowa based vaccine manufacturer was willing to produce vaccines at 1.2 cents/dose for the USDA. Finally, during the survey farmers reported that including labor costs vaccines can be acquired and administrated at 5 cents/dose. The estimated 5 cents per doze are used in the simulation. Only one doze is needed per bird. The solutions are presented in the table 3.10 below.

Table 3.10 Costs of the Outbreak without Any Demand Shift

Note: Results are in million U.S dollars.

The following important findings are obtained when the consumption level stay the same during the outbreak (no demand shift).

- The welfare loss in terms of producers' and consumers' surpluses is negligible compared to the mitigation cost. Most of the outbreak cost is in the mitigation costs. In District 8-N, the total outbreak cost is \$49.998 million with only \$0.008 million and \$0.046 million as losses in producers' and consumers' surpluses respectively. In the District 5-N, the total outbreak cost is \$42.478 million with only \$1.77E-4 million losses in producers' surplus and \$8.00E-5 million losses in consumers' surplus. In the less dense sub-region (District 5-S), the total outbreak cost is \$28.890 with only 3.14E-4 million and \$4.15E-4 million in producers' and consumers' surpluses respectively.
- When vaccination is used, the total outbreak cost drops to \$47.166 million in District 8-N, \$41.953 million in District 5-N and \$28.246 in District 8-N. In other words, there is a saving of \$2.832 million in District 8-N, \$1.939 million in District 5-N and \$1.601 million in District 8-N. These savings are higher if the outbreak occurs in the densest region. The savings are imputable to the reduction of the quantity of dead flocks during the outbreak if vaccination strategy is implemented. For instance without vaccination in District 8-N, the supply shock caused by depopulated and quarantined flocks will reduce total egg supply by 0.18% but with vaccination, the shock will reduce the total egg supply by 0.00074%. This implies that the vaccination strategy significantly reduces the impact of the outbreak.

• Prices stayed at their levels prior to the outbreak since the supply shocks were not big enough to significantly shift the supply curves.

Next, we estimated the costs of the AI outbreak if shifts in demand curves occur as a result of media coverage of the outbreak. Due to limited AI outbreak in the U.S, studies regarding the impact of AI outbreak on the U.S demand for poultry products are rare or nonexistent. A study that investigates the impact of AI outbreak on poultry product consumption in Italy found that the outbreak reduced domestic demand for fresh poultry by 22% in average (Beach et al, 2008). Further, the study showed that due to similarities and differences between Italian and the U.S economy, an outbreak in the U.S may have smaller or larger impact. The simulation scenarios in table 3.11 below uses 10%, 20% and 30% to represent small, medium and large demand shift to analyze the welfare impact of the outbreak.

		Without Vaccination			With Vaccination	
	District 8-N	District 5-N	District 5-S	District 8-N	District 5-N	District 5-S
Initial Welfare	9739.019	9739.019	9739.019	9739.019	9739.019	9739.019
Small shock (10%)						
New Welfare	7766.003	7773.392	7786.981	7768.695	7775.339	7788.582
Total Cost	1973.016	1965.627	1952.038	1970.324	1963.680	1950.437
Producer's cost	328.487	328.481	328.481	328.481	328.481	328.481
Consumer's cost	1594.707	1594.668	1594.668	1594.668	1594.668	1594.668
Mitigation cost	49.822	42.478	28.889	47.175	40.531	27.288
Medium shock (20%)						
New Welfare	6054.955	6062.340	6075.928	6057.643	6064.286	6077.529
Total Cost	3684.064	3676.679	3663.091	3681.376	3674.733	3661.490
Producer's cost	618.566	618.560	618.560	618.560	618.560	618.560
Consumer's cost	3015.676	3015.642	3015.642	3015.642	3015.642	3015.642
Mitigation cost	49.822	42.478	28.889	47.175	40.531	27.288
Small shock (30%)						
New Welfare	4555.568	4562.949	4576.537	4558.252	4564.895	4578.138
Total Cost	5183.451	5176.070	5162.482	5180.767	5174.124	5160.881
Producer's cost	858.124	858.120	858.120	858.120	858.120	858.120
Consumer's cost	4275.505	4275.473	4275.473	4275.472	4275.472	4275.473
Mitigation cost	49.822	42.478	28.889	47.175	40.531	27.288

Table 3.11 Total Outbreak Costs under Demand Shifts Scenarios

Note: Results are in million U.S dollars

The following results are found under the three demand shifts scenarios:

- Mitigation costs values are identical to the case without demand shifts but the total costs explode here due to substantive losses in producers' and consumers' surpluses. In the densest sub-region (District 8-N), the total outbreak costs become \$1,973.016 million under a small demand shift (10%) scenario with losses in producers' and consumers' surplus being respectively \$328.487 million and \$1,594.707 million. Under medium demand shift scenario, the total costs will be \$3,684.064 million with losses in producers' and consumers' surplus being respectively \$618.566 million and \$3,015.676 million. Under large demand shift scenario, the total cost will be \$5,183.451million with losses in producers' and consumers' surplus being \$858.124 million and \$4,275.505 million. These total costs will decrease if the outbreak occurs instead in the less dense sub-regions (District 5-N and District 5-S) but the cost are substantively higher comparatively to the case without demand shift.
- Similarly to the case without demand shift, the vaccination strategy reduces the mitigation costs but generates similar losses in consumers' and producers' surpluses. As we can see in table 3.11 above, except that mitigation costs are reduced under vaccination strategy, other total costs components stay identical with and without vaccination.
- Here price levels have changed due to demand shifts. Because of the zoonotic nature of this disease, significant media coverage will likely create a demand

shift that can lower prices. Table 12 below gives the price dynamic consistent with demand shift scenarios.

Prices	Egg	Chicken	Turkey
Pre-outbreak levels	1.031	1.518	1.045
Small shift (10%)	0.938	1.388	0.941
Percentage change	$-9%$	$-8.5%$	$-9.9%$
Medium shift (20%)	0.846	1.259	0.837
Percentage change	$-18%$	$-17%$	$-19.9%$
Large shift (30%)	0.753	1.129	0.774
Percentage change	$-26.9%$	$-25.6%$	$-25.9%$

Table 3.12 Price Changes in the Three Demand Shift Scenarios

Note: Egg prices are in dollars per dozen, chicken and turkey prices are in dollars per pounds.

Under small demand shift scenario egg prices will drop about 9%, chicken prices will drop about 8.5% and turkey prices will drop about 9.9%. Under medium demand shift scenario, egg, chicken and turkey prices will drop respectively about 18%, 17% and 19.9%. Lastly under the large demand shift scenario, egg price will drop about 26.9%, chicken prices will drop about 25.6% and turkey prices will drop about 25.9%. Recall that without demand shifts, an outbreak in Texas will not have a significant impact on prices. The reason is that Texas production is a small proportion of the national production and cannot provoke a significant drop in supply.

Next, empirical results of decision making under uncertainty for ex-ante investment are presented.

3.5 Empirical Results of Pre-event Vaccines Investment Decision Making

This subsection answers the question of whether it is economically optimal to invest in vaccines prior to the outbreak. This question is addressed from the perspective of outbreak probability threshold level at which this investment should be made. The critical information needed to solve this problem is the fixed investment cost to be made prior to the outbreak.

The Center for Infectious Disease Research and Policy (CIDRAP, 2005) reported on their website that an Iowa based vaccine manufacturer (Fort Dodge Animal Health) signed a contract with USDA in 2005 to produce 40 million doses of AI vaccines for \$800,000 and these vaccines can be stored frozen for 5 years. After this investment each additional dose would cost about 1.2 cents. The FAO (Smith, 2007) also reported that vaccines can be produced by a China based company at 1.2 cents per dose.

Using these numbers for Texas poultry industry where the total population of birds is roughly 20 million, the fixed investment cost would be about the half of the investment made by the USDA or \$400,000.

After solving the decision making problem described in the last subsection of section 2, pre-event investment in vaccines will be economically optimal if the probability of AI outbreak in any of the sub-regions is bigger than 0.07. This result suggests that for any positive probability comprised in the interval of [0.07, 1], an exante investment in vaccines production and stocking could be made. When this analysis is conducted for each district separately, the results showed that ex-ante investment in vaccines will be economically optimal if the probability of outbreak is bigger than 0.39

in District 8-N, 0.61 in District 5-N and 0.68 in District 5-S. Intuitively, this results suggested that the higher the damage the lower the outbreak probability threshold will be.

3.6 Summary

Hypothetical AI outbreak impact on the US poultry industry and households have been studied under disease mitigation strategies with vaccination and without vaccination. Exante investment decision in vaccines was also analyzed. The outbreak costs vary depending on the density of the poultry sub-region and on whether demand shocks during the outbreak are negligible, small, medium or large.

If the demand shock during the outbreak is negligible, the total outbreak costs depend only on the mitigation costs and prices will be at their base level. An outbreak in the District 8-N will cost about \$49.998 million dollars and an outbreak in the District 5- N and the District 5-S will cost respectively \$42.478 million and \$28.890 million. Should vaccination strategy be used, the total costs in the District 8-N will be reduced by \$2.832 million, the total costs in the District 5-N will be reduced by \$1.939 million and the total costs in the District 5-S will be reduced by \$1.601 million. The advantage of the vaccination strategy is that it reduces the number of quarantined and culled flocks.

If the demand shock is not negligible, three scenarios of demand shocks of 10% (small shock), 20% (medium shock) and 30% (large shock) have been studied. In these cases, the total costs increase dramatically due to significant losses in producers' and consumers' surpluses in the poultry market. For instance, if the demand shock is small (10%), the total costs of an outbreak in the District 8-N will be about \$1,973.016 million

with \$328.487 million losses in producers' surplus. The total costs in the District 5-N will be about \$1,965.627 million with \$328.481 million in producers' surplus. Lastly the total costs in District 5-S will be about \$1,952.038 million with \$328.481 million in producers' surplus. These costs increase when the demand shocks are medium or large. Consistent with the results without demand shocks, the vaccination strategy reduces the total cost by lessening the mitigation cost. The other costs components related to the loss in consumers' and producers' surpluses remain identical to the case without vaccination being used.

Negative demand shocks during the outbreak reduce poultry products market prices. This study found that under a small shock scenario, egg prices will drop about 9% of the pre-outbreak level. Chicken and turkey prices will drop about 8.5% and 9.9% respectively. Under a medium demand shock scenario, egg price will drop about 18% while chicken and egg prices will drop about 17% and 19.9% respectively. Under a large demand shock scenario, egg price will drop about 26.9% while chicken and turkey will drop about 25.6% and 25.9% respectively.

Finally, the study found that the ex-ante investment decision in vaccines production is economically optimal if the probability of occurrence of the AI outbreak in Texas is 7%. Given that ex-ante vaccines investment cost (\$0.4 million) is reasonably lower than the gain in vaccination strategy ex-post (the minimum gain being \$1.939) million), it will be economically recommended to invest ex-ante in vaccines should the outbreak threat be high enough.

4. EVALUATING THE COSTS OF AI OUTBREAK IN TEXAS: A STOCHASTIC ANALYSIS APPROACH

This section examines the effects of considering risk and risk aversion in the integrated economic-epidemic model accounting for the stochastic spread nature of the disease. Indeed, the epidemic model contains risky parameters that are not known with certainty. Risky parameters in the epidemic model are the degree of damages as affected by the uncertain probability of effective contacts between infectious flocks and susceptible flocks.

The objective of the work in this section is to examine the effects of including risk on the results of the integrated economic-epidemic model. To achieve this objective, distributions of the epidemic risky parameters are estimated and Monte Carlo simulation is used to obtain probabilistic distributions of the total cost of a hypothetical AI outbreak. This approach follows closely the methodology of risk analysis proposed by Pouliquen (1983) who suggested that the estimated results be associated with their likelihood of occurrence or with confidence intervals.

The remainder of this section is organized as follows. Section 2 presents estimates on the parametric cumulative distribution functions (CDF) of the risky parameters. Section 3 uses these distributions with Monte Carlo simulation to estimate confidence intervals of the costs of a hypothetical AI outbreak in Texas. Section 4 revisits the ex-ante vaccines production decision making problem but addresses it in a risk framework. Section 5 concludes the section.

4.1 Estimating the Cumulative Distribution Functions of the Risky Parameters Two sets of risky parameters are present in the epidemic model. The first set is the infectious symptomatic probability of effective contact, and the second set is the infectious latent probability of effective contact.

 As shown in tables 3.5 and 3.6, probabilities of contact between the five types of flocks are used to construct 25 observations data in each sub-region. These 25 observations are utilized to estimate parameters for 10 parametric distributions including Double Exponential, Exponential, Gamma, Logistic, Log-Log, Log-Logistic, Lognormal, Normal, Pareto and Uniform. Parameters of each of these distributions were estimated using Maximum Likelihood (ML) estimation methods. The ML estimated parametric distributions were compared with the empirical distributions

 $(F(x)) = P(X_i \leq x)$ of the same data. The closest parametric distribution to the empirical distribution is selected using a version of the Anderson-Darling (1952) goodness-of-fit test. The various steps used in the estimation of these parametric distributions follow Richardson (2008).

The version of Anderson-Darling test used here is designed to penalize the distribution at the tails in order to select the closest distribution to the empirical distribution not only at the mean but also at the tails. The formula for the test is given below.

$$
A = \int_{-\infty}^{\infty} \left[(F_n(x) - \hat{F}_n(x))^2 + (F_n(x) - \hat{F}_n(x))^2 * I(X_i < \overline{X} - \sigma) + (F_n(x) - \hat{F}_n(x))^2 * I(X_i > \overline{X} - \sigma) \right] \rho_x \hat{f}(x) dx
$$
\nwhere

\n
$$
\theta_x^2 = \frac{1}{\hat{F}_n(x)(1 - \hat{F}_n(x))} \text{ is a weight function}
$$
$\hat{f}_n(x)$ is an estimated parametric density function and $I(\bullet)$ is an indicator function. The statistic *A* of this test is compared to the perfect fit of $A = 0$. The best fit is the parametric distribution for which *A* is the closest to 0. In the formula above, the expression $(F_n(x) - \hat{F}_n(x))^2 * I(X_i < \overline{X} - \sigma)$ adds a penalty when the estimated parametric distribution deviates from the true distribution at the left tail. The expression $(F_n(x) - \hat{F}_n(x))^2 * I(X_i > \overline{X} - \sigma)$ adds a penalty at the right tail.

The results of the estimation presented in table 4.1 below are based on sample sizes larger than the 25 observations generated though bootstrapping. Since consistency of maximum likelihood estimators relies on asymptotic properties (Pawitan, 2001), bootstrap samples are obtained through 1000 draws with replacement from the original sample of 25 observations. Efron (1979) and Efron and Tibshirane (1993) recommended a minimum of 250 observations for this type of bootstrap. These bootstrap samples have the same means as the original data but their variances are smaller because of the larger sample size.

The Anderson-Darling test statistics for eight of the ten parametric distributions enumerated above are presented in the table 4.1 below. Parameters for Gamma and logistic distributions are inconsistent with most of the data and therefore those results are not presented here.

	Infected Effective Contacts				Latent Effective Contacts				
	District8-N	District5-N	District5-S	Texas	District8-N	District5-N	District5-S	Texas	
Double									
Exponential	0.0074	0.0732	0.1013	0.0013	0.0002	$9.6E - 0.5$	0.0029	$2.1E-05$	
Exponential	0.0057	0.0644	0.0996	0.0010	0.0001	2.5E-05	0.0019	$1.3E-05$	
$Log-Log$	0.0062	0.0674	0.1009	0.0011	0.0001	3.6E-05	0.0022	$1.6E-05$	
Log-									
Logistic	0.0106	0.0689	0.0812	0.0014	0.0074	0.0161	0.0487	0.00056	
Lognormal	0.0045	0.0638	0.0869	0.0009	0.0009	0.0010	0.0066	6.5E-05	
Normal	0.0068	0.0769	0.0982	0.0012	0.0001	$4.1E-05$	0.0023	$1.6E-05$	
Pareto	65364	393207	$2.E+13$	82462.	$2.E+13$	$5.1E + 11$	$3.E+14$	$3.3E+12$	
Uniform	0.0245	0.2689	0.0945	0.0044	0.0002	4.1E-05	0.0042	2.9E-05	
Parameter1	-5.50821	-5.4190	1.1445	-7.2420	0.0065	0.0063	0.0178	0.00700	
Parameter 2	1.5671	1.6584	0.0022	1.7970	$4.E-05$	4.0E-05	0.0003	5.5E-05	

Table 4.1 Anderson-Darling Goodness-of-fit Statistics

Note: parameter 1 and parameter2 are the estimated parameters for the best parametric distribution selected. The test statistics of best parametric distributions are in bold.

The results above indicate the lognormal distribution is the best fit for the probability of effective symptomatic flocks contacts in District 8-N and District 5-N while the log-logistic distribution provides the best fit for the District 5-S data. For the probability of latent effective contacts data, the exponential distribution provides the best fit in the three sub-regions.

4.3- Monte Carlo Simulation Results of the Cost of AI Outbreak

The integrated model was solved simulating stochastic probabilities of effective contacts under four alternative demand shock scenarios (0% demand shock, a small shock of 10% demand shift, a medium shock of 20% shift and a large shock of 30% demand shift). Random draws of 256 observations from each parametric distribution are used in the simulation of the model for each sub-region. Experimentation showed 200 iterations are found to be sufficient as increasing the number of draws beyond 200 does not change the distribution of the key output variables. These outputs are used to estimate 95% confidence intervals and to plot Kernel cumulative distribution functions (CDF) of the total costs under the two alternative mitigation strategies. Once these CDFs are obtained, stochastic dominance criteria are used to rank the costs under the two alternative mitigation strategies following Meyer (1977), McCarl (1988) and Hardaker et al. (2004). The strategy that dominates in the stochastic dominance sense is the cost effective strategy in our model. The table 4.2 below gives the average total outbreak cost and the 95% confidence intervals for the District 8-N under the four demand shock scenarios discussed previously. Separate results are compiled for each sub-region.

	Without Vaccination			With Vaccination			
	Mean	95% Confidence interval		Mean	95% Confidence interval		
No Shock (0%)		Lower	Upper		Lower	Upper	
Producer's cost	0.066	[0.000,	0.165]	0.060	[0.000]	0.163]	
Consumer's cost	0.497	[0.000,	1.336]	0.460	[0.000]	1.336]	
Mitigation cost	44.569	[28.010,	49.982]	42.918	[27.526]	47.217]	
Total Cost	45.089	[29.616,	49.981]	43.438	[29.122]	47.218]	
Small shock (10%)							
Producer's cost	328.543	[328.481]	328.637]	328.537	[328.481]	328.636]	
Consumer's cost	1595.117	[1594.668,	1595.870]	1595.084	[1594.668]	1595.870]	
Mitigation cost	28.010	[28.010,	49.9821	42.915	[27.526]	47.217]	
Total Cost	1968.184	[1952.612,	1973.131]	1966.537	[1952.117]	1970.366]	
Medium shock (20%)							
Producer's cost	618.623	[618.560]	618.716]	618.614	[618.560]	618.707]	
Consumer's cost	3016.073	[3015.642]	3016.772]	3016.012	[3015.642]	3016.709]	
Mitigation cost	43.999	[27.476]	49.9861	42.914	[27.526]	47.217]	
Total Cost	3678.695	[3662.999]	3684.1891	3677.540	[3663.016]	3681.419]	
Large shock (30%)							
Producer's cost	858.168	[858.120,	858.2421	858.161	[858.120]	858.2351	
Consumer's cost	4275.864	[4275.472,	4276.4671	4275.809	[4275.472]	4276.411]	
Mitigation cost	43.999	[27.502]	49.987]	42.912	[27.526]	47.217]	
Total Cost	5178.030	[5162.261]	5183.580]	5176.882	[5162.255]	5180.808]	

Table 4.2 Total Costs in District 8-N: Means and 95% Confidence Intervals

Note: The estimated costs are in millions of US dollars

The results of the table 4.2 are interpreted below as follows:

- With no demand shock and no vaccination, there is 50% likelihood that the total cost will be less than or equal to \$45.1 million. There is 95% confidence that the total cost of the outbreak will be between \$29.6 million and \$50 million. Should the vaccination strategy be used there is 50% likelihood that the total cost be less or equal to \$43.4 million and the 95% confidence interval is narrower ranging from \$29.1 million and \$47.2 million.
- With a 10% demand shock and no vaccination strategy used, there is 50% likelihood that the total cost will be less than or equal to \$1,968 million and there is 95% confidence that the total cost will be between \$1,953 million and \$1,973 million. That confidence interval will be narrower if vaccination is used and the average total cost lower. In this case, there is 50% likelihood that the total cost will be less or equal to \$1,967 million and the confidence interval will be between \$1,952 million and \$1970 million.
- With 20% demand shock and no vaccination strategy used, there is 50% likelihood that the total cost will be less or equal to \$3,679 million and the 95% confidence interval will be between \$3,663 million and \$3,684 million. With vaccination strategy used, there is 50% likelihood that the total cost will be less or equal to \$3,677 and the 95% confidence interval will be between \$3,663 million and \$3,681 million.
- Finally, with a 30% demand shock and no vaccination, there is 50% likelihood that the total cost will be less or equal to \$5,178 million and the 95% confidence

interval will be between \$5,162 million and \$5,184 million. Under vaccination, there is 50% likelihood that the total cost will be less or equal to \$5,177 million and the 95% confidence interval of the total cost will be between \$5,162 million and \$5,159 million.

To represent visually the above findings in terms of stochastic dominance,

figures 4.1 to 4.4 show the cumulative distribution functions of the total cost.

Figure 4.1 District 8-N: total cost distributions under 0% demand shock

Figure 4.2 District 8-N: total cost distributions under 10% demand shock

Figure 4.3 District 8-N: total cost distributions under 20% demand shock

Figure 4.4 District 8-N: total cost distributions under 30% demand shock

Figures 4.1 to 4.4 show that the proposed vaccination strategy dominates the current strategy by first degree stochastic dominance. That is, there are higher frequencies of realization of lower cost under vaccination strategy than a no vaccination strategy. Next, similar analyses are presented for the sub-region of the District 5-N.

	Without Vaccination			With Vaccination			
	Mean	95% Confidence interval		Mean	95% Confidence interval		
No Shock (0%)		Lower	Upper		Lower	Upper	
Producer's cost	0.027	[0.000,	1.000]	0.023	[0.000,	0.098]	
Consumer's cost	0.211	[0.000,	0.920]	0.183	[0.000,	0.922]	
Mitigation cost	40.562	[30.174,	42.547]	39.073	[29.662,	40.607]	
Total Cost	40.799	[31.204,	42.548]	39.279	[30.695,	40.609]	
Small shock (10%)							
Producer's cost	328.506	[328.481,	328.576]	328.502	[328.481]	328.575]	
Consumer's cost	1594.859	[1594.668,	1595.496]	1594.834	[1594.668,	1595.497]	
Mitigation cost	40.560	[30.173,	42.547]	39.071	[29.661,	40.607]	
Total Cost	1963.925	[1954.255,	1965.696]	1962.407	[1953.745,	1963.757]	
Medium shock (20%)							
Producer's cost	618.584	[618.560,	618.650]	618.580	[618.560,	618.650]	
Consumer's cost	3015.812	[3015.642,	3016.378]	3015.790	[3015.642,	3016.379]	
Mitigation cost	40.559	[30.173,	42.547]	39.140	[29.970,	40.879]	
Total Cost	3674.955	[3665.209,	3676.749]	3673.510	[3665.009,	3675.081]	
Large shock (30%)							
Producer's cost	858.139	[858.120,	858.1991	858.137	[858.120,	858.199]	
Consumer's cost	4275.626	[4275.472,	4276.1221	4275.606	[4275.472,	4276.124]	
Mitigation cost	40.557	[30.173,	42.547]	39.140	[29.970,	40.879]	
Total Cost	5174.323	[5164.503,	5176.140]	5172.883	[5164.303,	5174.472]	

Table 4.3 Total Costs in District 5-N: Means and 95% Confidence Intervals

Note: The estimated costs are in millions of US dollars.

If the outbreak occurs in the District 5-N, the outbreak cost results given in the table 4.3 above under the four demand shift scenarios are interpreted as follows:

- With no demand shock, there is 50% likelihood that the total cost will be less or equal to \$40.8 million and the 95% confidence interval will be between \$31.2 million and \$42.5 million. When vaccination strategy is used, there is 50% likelihood that the total cost will be less or equal to \$39.3 millions and the confidence interval will be between \$30.7 million and \$40.6 million.
- With 10% demand shock, there is 50% likelihood that the total cost will be less or equal to \$1,964 million and the 95% confidence interval will be between \$1,954 million and \$1,966 million. Should the vaccination strategy be used, there is 50% likelihood that the total cost will be less or equal to \$1,962 million and the 95% confidence interval will be between \$1,954 million and \$1,964 million.
- With 20% demand shock, there is 50% likelihood that the total cost will be less or equal to \$3,675 million and the 95% percent confidence interval will be between \$3,665 and \$3,677 million. When vaccination strategy is used, there is 50% likelihood that the total cost will be less or equal to \$3,674 million and the 95% confidence interval will be between \$3,665 million and \$3,675 million.
- With 30% demand shock, there is 50% likelihood that the total cost will be less or equal to \$5,174 million and the 95% confidence interval will be between \$5,165 million and \$5,176 million. When vaccination strategy is used, there is 50% likelihood that the total cost will be less or equal to \$5,164 and the confidence interval will be between \$5,164 and \$5,174 million.

To analyze these results in terms of stochastic dominance criteria, cumulative distribution functions of total outbreak costs under the four demand shock scenarios for both strategies are given in figure 4.5 to 4.8 below.

Figure 4.5 District 5-N: total cost distributions under 0% demand shock

Figure 4.6 District 5-N: total cost distributions under 10% demand shock

Figure 4.7 District 5-N: total costs distributions under 20% demand shock

Figure 4.8 District 5-N: total costs distributions under 30% demand shock

Similar to the results obtained from Districts 8-N, vaccination strategy first degree stochastically dominates the current strategy under the four demand shift scenarios. Next, CDF plots of the total outbreak cost in the less dense sub-region (District 5-S) are presented under the four demand shifts scenarios.

		Without Vaccination		With Vaccination			
	Mean	95% Confidence interval		Mean	95% Confidence interval		
No Shock (0%)		Lower	Upper		Lower	Upper	
Producer's cost	0.032	[0.000,	0.092]	0.026	[0.000,	0.086]	
Consumer's cost	0.204	[0.000,	0.604]	0.173	[0.000,	0.595]	
Mitigation cost	27.045	[20.006,	28.926]	25.950	[19.619,	27.335]	
Total Cost	27.281	[20.670,	28.928]	26.148	[20.281,	27.337]	
Small shock (10%)							
Producer's cost	328.511	[328.481,	328.562]	328.506	[328.481,	328.559]	
Consumer's cost	1594.856	[1594.668,	1595.187]	1594.831	[1594.668,	1595.187]	
Mitigation cost	26.972	[21.142,	28.951]	25.883	[20.747,	27.350]	
Total Cost	1950.339	[1944.873,	1952.101]	1949.220	[1944.479,	1950.502]	
Medium shock (20%)							
Producer's cost	618.588	[618.560,	618.637]	618.583	[618.560,	618.633]	
Consumer's cost	3015.810	[3015.642,	3016.1031	3015.787	[3015.642]	3016.102]	
Mitigation cost	26.971	[21.142]	28.951]	25.882	[20.747,	27.349]	
Total Cost	3661.369	[3655.865]	3663.154]	3660.253	[3655.470,	3661.553]	
Large shock (30%)							
Producer's cost	858.139	[858.120,	858.170]	858.136	[858.120,	858.170]	
Consumer's cost	4275.630	[4275.473,	4275.889]	4275.607	[4275.473,	4275.889]	
Mitigation cost	26.970	[21.142,	28.951]	25.881	[20.747,	27.349]	
Total Cost	5160.738	[5155.195,	5162.545]	5159.624	[5154.801,	5160.943]	

Table 4.4 Total Costs in District 5-S: Means and 95% Confidence Intervals

Note: The estimated costs are in millions of US dollars.

If the outbreak occurs in the less dense sub-region of District 5-S, depending on the demand shock scenarios, the total outbreak cost and the table 4.4 above are interpreted as follows:

- Without demand shift, there is 50% likelihood that the total cost will be less or equal to \$27.3 million and the 95% confidence interval will be between \$20.7 million and \$28.9 million. If vaccination strategy is used, there is 50% likelihood that the total cost will be less or equal to \$26.1 million and the 95% confidence interval will be between \$20.3 million and \$27.3 million.
- With 10% demand shock, there is 50% likelihood that the total cost will be less or equal to \$1,950 million and the 95% confidence interval will be between \$1,944 million and \$1,951 million. If vaccination strategy is used, there is 50% likelihood that the total cost will be less or equal to \$1,949 million and the confidence interval will be between \$1,944 million and \$1,951 million.
- With 20% demand shock, there is 50% likelihood that the total cost will be less or equal to \$3,661 million and the 95% confidence interval will be between \$3,656 million and \$3,663 million. If vaccination strategy is used, there is 50% likelihood that the total cost will be less or equal to \$3,660 million and the 95% confidence interval will be between \$3,655 million and \$3,662 million.
- With 30% demand shock, there is 50% likelihood that the total cost will be less or equal to \$5,161 million and the 95% confidence interval will be between \$5,155 million and \$5,163 million. If the vaccination strategy is used to control the outbreak, there is 50% likelihood that the total cost will be less or equal to

\$5,160 million and the 95% confidence interval will be between \$5,155 million and \$5,161 million.

To visualize the above results in District 5-S and rank in terms of first degree stochastic dominance, the total cost under both strategies are presented in figure 4.9 to 4.12 below.

Figure 4.9 District 5-S: total costs distributions under 0% demand shock

Figure 4.10 District 5-S: total costs distributions under 10% demand shock

Figure 4.11 District 5-S: total costs distributions under 20% demand shock

Figure 4.12 District 5-S: total costs distributions under 30% demand shock

Consistently with results showed in the other sub-regions, the vaccination strategy first degree stochastically dominates the current strategy under the four demand shift scenarios.

4.4 Ex-ante Vaccines Investment Decision under Stochastic Epidemic Spread Model

In the following, results of the ex-ante investment in vaccines production decision are obtained under the hypothesis that the disease spreads through stochastic contacts. The assumption regarding the fixed investment cost is identical as in the previous section where the value of \$0.4 million fixed investment cost is used in the estimation. Here, the threshold probabilities are estimated for the entire State of Texas (Combining all the districts) and each of the three districts separately. The obtained simulation results show that the threshold probabilities above which an ex-ante investment in vaccines could be made vary with the disease transmission parameters. The density of the threshold outbreak probability for Texas is given in the figure 4.13 below.

Figure 4.13 Distribution of the threshold probability in Texas

Simulated results for all Texas districts in figure 4.13 show that the threshold probability is 0.07 with 82% likelihood. That is, over 100 simulations of the contact rates, the threshold probability of 0.07 occurs 82 times and other higher threshold probabilities occur 18 times. In fact, the threshold of 0.11occurs with 12% likelihood and threshold of 0.14, 0.21 and 0.32 have equally likelihood of 2% to occur.

Each district simulated separately shows that the threshold probabilities above which investment in vaccines should be made are respectively 0.39(or 0.40) in District 8-N with 67% likelihood, 0.61 in District 5-N with 78% likelihood and 0.68(or 69) in District 92% likelihood. Figures 4.14 to 4.16 below are the densities of the threshold probabilities in the three districts separately.

Figure 4.14 District 8-N: distribution of the threshold probability

Figure 4.15 District 5-N: distribution of the threshold probability

Figure 4.16 District 5-S: distribution of the threshold probability

4.5 Summary

This section presented estimates of the total cost of a hypothetical outbreak in Texas under stochastic disease spread. Consistent with risk analysis methods, 95% confidence intervals are constructed and the two disease mitigation strategies are compared using stochastic dominance criteria. Depending on the demand shock scenarios the findings are summarized as follows.

The study show that in absence of a demand shift, vaccination reduces respectively the mean outbreak costs by \$1.6 million in District 8-N, \$1.5 million in District 5-N and \$1.1 million in District 5-S. Also, It narrows the range in particularly reducing the upper bound of the 95% confidence intervals respectively by \$2.7 million in District 8-N, \$1.9 million in District 5-N and \$1.6 million in District 5-S. The same type of results occur when demand shifts are factored in with the mean damage reduction being \$1.6, \$1.2, 1.1million under 10, 20 and 30% demand shifts respectively regardless of the district of outbreak. Similarly under the demand shifts scenarios, the range is reduced and the upper tail truncated.

The stochastic dominance results suggested that the vaccination strategy dominates the current strategy in first degree stochastic dominance sense. These results applied to each of the three Texas districts regardless of the demand shift scenarios and the risk aversion coefficient of the decision maker. In fact, risk aversion of the decision maker become relevant when there are crossings in the cumulative distributions of the total costs.

Finally, this section estimated the distribution of the critical outbreak probability above which an ex-ante investment in vaccines is worth making under a stochastic disease spread. The results suggested that in the face of the possibility of a simultaneous outbreak in all districts an ex-ante investment in vaccines should be made if the probability of the outbreak is greater than 0.07. The likelihood of this threshold is about 82%. If only individual outbreaks are considered, the thresholds will be respectively 0.39 in District 5-N with 60% likelihood, 0.61 in District 5-N with 78% likelihood and 0.68 in District 5-S with 92% likelihood.

5. CONCLUSION AND FUTURE RESEARCH OPPORTUNITIES

This dissertation did an economic-epidemic evaluation of alternative AI disease control strategies as an input to disease response planning efforts. Specifically the study evaluated two options:

- the current USDA recommended approach that establishes a quarantine zone in a 5-miles radius around the outbreak site within which every flock is depopulated, and then a varying surveillance radii around that zone plus movement restrictions and testing (Pelzel, McCluskey and Scott 2006); and
- an alternative mitigation strategy which is recommended by the World Animal Health Organization that vaccinates all susceptible flocks in near proximity to the quarantine zone in addition to the current strategy stated above (OIE 2007 and 2008).

To carry out this evaluation an integrated economic-epidemic model was developed and applied to a hypothetical outbreak in selected Texas poultry producing regions.

The total outbreak costs of the current and the vaccination strategies were estimated under deterministic and stochastic epidemic disease spread assumptions. Also, the outbreak probability that justifies ex-ante investment in vaccines was studied. Arising from this effort the following conclusions may be drawn:

- Vaccination reduces total outbreak costs compared to the currently recommended USDA strategy.
- The economic impact of an outbreak depends heavily on whether and by how much consumer demand for poultry products is affected during the outbreak.
- Not surprisingly AI outbreaks in sub-regions that have dense poultry populations yield more damages than less dense sub-regions.
- In the absence of a demand shift losses are largely comprised of disease control costs with the animal losses being rather small.
- When demand shifts, profit losses and consumers' surplus losses dramatically increase the total outbreak costs.
- under the possibility of a widespread outbreak across all Texas sub-regions it is optimal to invest ex-ante in vaccines production if the probability of the outbreak is greater than 0.07.
- If the outbreak is analyzed separately in each district, ex-ante investment in vaccines is optimal if the probabilities of outbreak are respectively 0.39 in District 8-N, 0.61 in District 5-N and 0.68 in District 5-S.

The contributions of this work are several:

- The modeling and analysis contribute to the analysis and understanding of the economic impact of animal diseases.
- The model developed integrates both the epidemic and the economic analysis simultaneously to an extent not done before in the AI context and provides a framework for future evaluations.
- The epidemic model includes control strategies that portray a more realistic representation of animal disease management.

• The use of partial equilibrium economic model allows analysis of disease effects across sub-regions details that a general equilibrium analysis framework could not incorporate.

The study is not without limitations. In particular the epidemic model was build by economists and could be improved with more work, data collection and disease understanding. Also, the lack of geographical information on poultry farms in Texas has limited the use of spatial modeling approach in the design of the epidemic model. Finally, the model has not directly included loss of international trade for some time and has not calculated the spill-over effect on substitutes for poultry products.

Future research could be conducted in two directions. First, a more comprehensive research epidemic model of the poultry sector could be developed to better support the economic analysis and model live bird markets and wildlife effects among other factors. In this regard, the use of geographic information systems (GIS) data to the extent available would be greatly beneficial. Second, the economic model could be expanded to allow examination of the implications of the AI outbreak on substitute products markets, feed markets, other regions and international trade. In this regard, the forestry and agricultural optimization model developed by McCarl et al. (2005) could be used.

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APPENDIX I

Source: USDA TEXAS HENS & PULLETS OF LAYING AGE: December 1, 2007 Inventory

APPENDIX II

CONTACT RATE SURVEY

1-How many weeks are the average cycle of your poultry production? ___________Weeks

2-How would you classify the size of your poultry operation? (Please check all that apply)

- o **Layers less than 400 birds**
- o **Layers comprise between 400 and 100,000 birds**
- o **Layers greater than 100,000 birds**
- o **Broilers**
- o **Turkeys**

3- If your operation is one or more of the above, please show how many times you send to other categories during an average cycle?

4- How many times do you receive from other categories during the average cycle?

5-What is the full capacity of your poultry feeding operation? _________________birds

6-What borders your premises? (Please check all that apply)

- o **Other poultry premises**
- o **River/Stream/lake**
- o **Open lands**
- o **Other______________________**

7-How many of your employees who work in your premise also raise chicken, turkey or other birds in their own home? (Please fill in the space or check box)

o **_______ Employees**

o **Don't know**

8- Are any of your employees allowed to work for other poultry producers? (Please check one)

o **Yes**

o **No**

9-If your answer is "yes" to the question above; please show the number of times per week that your employees go to other premises through the following table.

10- How often do the following visit your premise per average cycle?

11- Do the following visit only your premises or multiple other premises per trip? (Please check the correct answer).

12- If your answer is "no" to the question above, please show how many times the trucks leave your property to other premises per week through the following table.

13- Please show the movements of the veterinarian or the nutritionist from your property to other premises per average cycle through the following table.

14- What other precautions do you take to avoid disease spread in your property? (Please check those that applies)

- o **Plastic cloths and gloves for employees**
- o **Every employee must clean his hands before and after work**
- o **Clean the site after every production cycle**
- o **Other_________________________________**

15- If you answer one or more of the above, what is the estimated cost per average cycle?

16- If your animals was not infected but are constrained in a quarantine zone and no birds movements are allowed in or out, how much will you estimate your loses?

17- What is the projected monetary cost to pay work crews to vaccinate or test your birds one time?

18- In case of an outbreak how are you going to manage the carcasses disposal?

- o **Incinerate the carcasses**
- o **Bury the carcasses**
- o **Other_________________**

 19- If you choose one of the above options, how much can you estimate the cost?

___ ___ ___ ___ ___ ___ ___ ___

- o **Incinerate the carcasses___________**
- o **Bury the carcasses_______________**
- o Other

Comments

VITA

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