THREE ESSAYS ON BIO-SECURITY

A Dissertation

by

QI GAO

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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Approved by:

Chair of Committee,	Bruce A, McCarl
Committee Members,	David Bessler
	Ximing Wu
	Qi Li
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ABSTRACT

Three Essays on Bio-security.

(December 2009)

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Chair of Advisory Committee: Dr. Bruce A, McCarl

In this dissertation, several essays in the field of bio-security are presented.

The estimation of the probability of an FMD outbreak by type and location of premises is important for decision making. In Essay I, we estimate and predict the probability/risk of an FMD outbreak spreading to the various premises in the study area. We first used a Poisson regression model with adjustment dispersion associated with random simulation results from the AusSpead model to estimate the parameters of the model. Our estimation and prediction show that large cattle loss could be concentrated in three counties-Deaf Smith, Parmer, and Castro. These results are based on approximately 70% of the feedlots with over 10,000 cattle located in the three counties previously mentioned.

In Essay II, our objective is to determine the best mitigation strategies in minimizing animal loss based on AusSpead simulation model. We tested 15 mitigation strategies by using multiple comparison. The results show that the best mitigation strategies for all four scenarios are regular surveillance, slaughter of the infected animals, and early detection.

We then used the Mixed Integer Programming to estimate costs of disposing of animal carcasses and transportation. Results show that the unit disposal cost will vary with carcass scale and the unit transportation cost also varies with the distribution of the infected premises and disposal locations.

FMD seems to have varying impacts on equity markets. In Essay III, we studied returns at three different levels of the stock market. We determined results in a structural break, and then estimated the impact of the announcement of confirmed cases of FMD disease on the volatility of stock market returns by using a GARCH-Mean model. Our results show that the structure break occurs on the day with the largest number of confirmed cases for meat product firms rather than the day of the first confirmed case. We found that the conditional volatilities over the FMD period are higher than those over the sample period. The announcement of confirmed cases had the largest marginal impact on meat products. Investors may always consider maintaining a portfolio consisting of index funds or hedge funds.

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CHAPTER I

INTRODUCTION

1.1 Background

Concerns about invasive species and foreign animal diseases have escalated substantially in recent years. Terrorist attacks on the U.S. in September 2001 greatly increased the awareness of the vulnerability of U.S. agriculture to bioterrorism. In response to these concerns, President Bush signed into law the Public Health Security and Bioterrorism Preparedness and Response Act of 2002. The purpose of this Act is"To improve the ability of the United States to prevent, prepare for, and respond to bioterrorism and other public health emergencies" (107th Congress, 2002).

Foot-and-mouth disease (FMD) is a highly contagious viral disease of cloven-hoofed domestic and wild animals, such as cattle, bison, pigs, sheep, goats, and deer. Because FMD is highly contagious, it is arguably one of the most important livestock diseases in terms of economic impact throughout the world. It can be spread though air, transport vehicles, artificial insemination, milk-related transmission, direct contact, and by wildlife such as birds, dogs, cats, and rodents. Infected animals do not show the signs of the disease for a couple of weeks but are contagious during the latter part of that time (Bouma et al., 2003). This means the infected animals are spreading the disease before they are diagnosed and removed from the herd. Variations in weather, regional geography, farming practices,

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and farm-level bio-security practices could all introduce spatial and temporal heterogeneity into transmission patterns.

FMD outbreaks have proven to be costly because they have occurred throughout the world.A Taiwanese outbreak was estimated to cost (in U.S.) $187.5 million in 1997 (Yang et al., 1997). The U.K. FMD outbreak between February 20 and September 30, 2001 exhibited a total of 2,026 confirmed cases of FMD with the direct cost to the public sector estimated at over $3 billion and the cost to the private sector estimated at over $5 billion (National Audit Office (NAO), 2002). Compensation and other payments to farmers totaled nearly $1.4 billion, and direct costs of measures to deal with the epidemic, including the purchase of goods and services to eradicate the disease, amounted to nearly $1.3 billion. Other public sector costs were estimated at $0.3 billion. In the private sector, the areas most affected by the outbreak were agriculture, the food chain and supporting services, which incurred net costs of $0.6 billion, and tourism and supporting industries, which lost revenues of between $4.5 billion and $5.4 billion (National Audit Office(NAO): The 2001 Outbreak of Foot and Mouth Disease). The estimated net direct economic effect of the outbreak was less than $2 billion, 0.2 per cent of Gross Domestic Product. The net economic effect was less than the £ 5 billion cost to agriculture and tourism because many of the losses suffered by individuals and firms led to equivalent amounts being spent elsewhere in the economy (National Audit Office (NAO): The 2001 Outbreak of Foot and Mouth Disease).

In the U.S., FMD was first discovered in 1870. Since the initial outbreak, there have been eight additional outbreaks, with the last being a mild epidemic in California in 1929. In 1914, the U.S. had its most devastating FMD outbreak, which began in Michigan and spread to the Chicago stockyards by 1915. Overall, FMD had spread to 22 states, and 172,000 cattle, hogs, sheep, and goats were destroyed during the eradication program (Mc-

Cauley et al., 1979).

Ekboir (1999) applied input-output (I-O) methods to examine the potential effects of a FMD outbreak in California and calculated a range of losses of $8.5-$13.5 billion. A substantial share of those estimated effects, $6 billion, resulted from the assumption that U.S. meat exports would cease. Paarlberg and Seitzinger (2002) (2002) employed partial equilibrium analysis to determine the effects of an FMD outbreak in the United States similar to the 2001 outbreak in the United Kingdom. They estimate a U.S. farm income loss of $14.0 billion and a reduction in national consumer expenditure of 7%.

Texas is the largest cattle production state in the U.S., with more than 14 million cattle and calves produced annually. The largest source of Texas agricultural revenue comes from the sale of beef cattle. Texas produces about 20% of the nation's beef cattle and ranks number one in the country in the value of cattle raised. With an estimated 6 million cattle on feed, the Texas feedlot industry is valued at more than $8 billion annually, according to U.S. Department of Agriculture: National Agricultural Statistics Service, "Texas State Agriculture Overview, 2004," January 3, 2006. The predominant concentration of the feedlot industry in Texas is within the Panhandle region.

The High Plains study region comprises a 5-county area in the Panhandle of Texas (Figure 1). This area covers 7,942 square miles, and according to the Texas Commission on Environmental Quality (TCEQ), which is responsible for maintaining records on concentrated animal feeding operations (CAFOs) (including feedlots and dairies), there are 92 feedlots and 76 dairies in the study area. The feedlots range in size from 10,000 to over 100,000 cattle. Spatial estimates of the study area grazing beef cattle were developed using land parcel data from the USDA Farm Services Agency (FSA) and the estimated carrying capacity from the National Resources Range Capacity guides. An estimated 411,019

grazing beef cattle are distributed over 10,000 land parcels in the study region (Ward et al., 2004).

1.2 Objectives

Ex-ante risk analysis and ex-post response actions are important issues for animal disease management. Ex-ante efforts are designed to prevent or reduce the probability of certain classes of attacks, while ex-post efforts involve rapid response to attacks and the minimization of associated damages. In the absence of a wealth of observable data on FMD outbreaks, disease modeling is the main tool for predicting the likely spread of the disease and for evaluating the effectiveness of various mitigation strategies (Bates et al., 2003). In this study, we used a disease model to conduct ex-ante analysis, including vulnerability and carcass disposal analysis, and ex-post response effects on the stock market in the U.K.

The objectives of this study are to contribute to ex-ante analysis, including vulnerability and carcass-disposal analysis by simulation model because of the absence of observable data on FMD outbreaks ex-post response on the stock market in the U.K.

The thesis is organized as follows. The objectives of Chapter II are to identify vulnerable areas and predict expected cattle loss under different scenarios. To achieve these goals, we used a Poisson regression model with adjustment dispersion associated with random simulation results from the AusSpead model to estimate the parameters of the model given one location as the starting point in the simulation, and we predicted the probability/risk and expected cattle loss of an FMD outbreak spreading to the premises given other premises as starting points in the study area.

The aim of Chapter III is to test the best mitigation strategies with average minimum

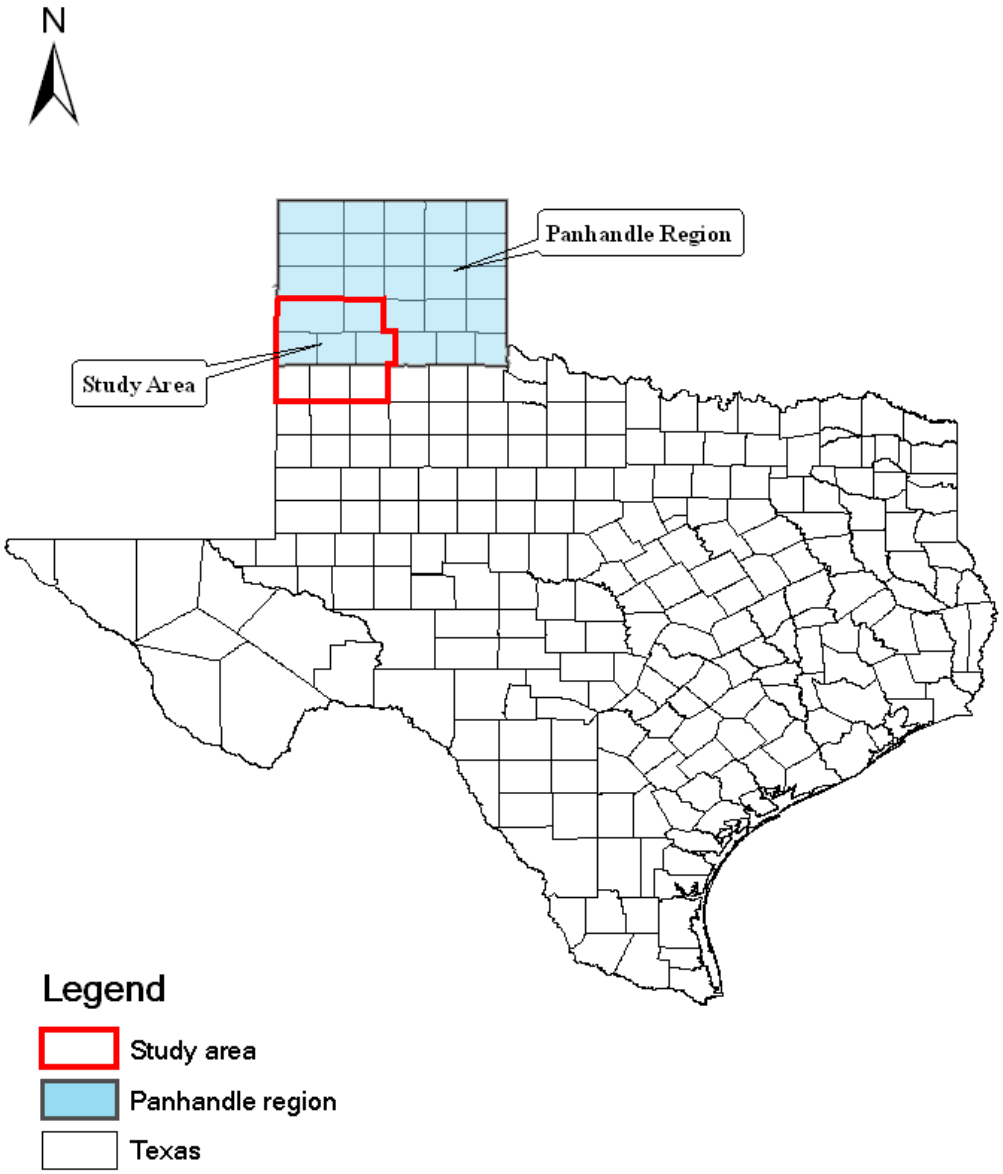


Figure 1: High Plains Study Area

animal loss and under the best strategy. We make preparation for the ”worst” status, estimating costs of disposing of animal carcasses and transportation following a largest FMD outbreak under four different scenarios, and examining the effectiveness of disposal strategies. To achieve the goal, we tested 15 mitigation strategies based on simulation results by multiple comparison and the best strategy group, then we selected one of the best mitigation strategies for four different scenarios and estimated minimum costs of disposing of animal carcasses and transportation.

The objective of Chapter IV is to measure how different impacts of the FMD among entire financial markets, the food product and retail industry, and individual food product companies represented individual food companies. It may help investors to understand the risk and build accurate asset pricing models that will yield superior forecasts for return volatility. To achieve this goal, we first used summary statistics and univariate GARCH to generally describe those six markets, then we applied a modified GARCH-in mean model to measure the different impacts of the announcement of confirmed cases by government agencies or public media.

CHAPTER II

IDENTIFYING VULNERABLE AREAS

2.1 Introduction

FMD has not been present in the United States since 1929. However, recent outbreaks in previously disease-free countries (including Japan, South Korea, France, the Netherlands, and the U.K.) have highlighted the importance of well-planned response strategies for regaining disease freedom after an outbreak, as well as for minimizing costs and facilitating recovery following an incursion of FMD (Garner and Beckett, 2005).

The estimation of the probability of FMD outbreak by type and location of premises is important for decision making. There are over 10,000 premises in the study area, each of which has a different probability for FMD occurrence. This chapter proposes to estimate and predict the probability/risk of FMD outbreak spreading to the premises in the study area. Specifically, our objectives are to identify vulnerable areas and to predict expected cattle loss under different scenarios. To achieve those goals, we used a Poisson regression model with adjustment dispersion associated with random simulation results from the AusSpead model to estimate the parameters of the model given one location as a start point in the simulation, and we predict the probability/risk and expected cattle loss of FMD outbreak spreading to the premises given other premises as start points in the study area.

2.2 Review of AusSpread

2.2.1 Conceptual Review of AusSpread

AusSpread is a state-transition model that has been developed based on Markov chain concepts with modifications to include stochastic elements in the transition (disease spread) probabilities (Garner and Beckett, 2005). Stochastic elements are represented as probability distributions, which incorporate the uncertainty or natural variation inherent in particular model parameters. Monte Carlo methods are used to select values from these probability distributions each time that the model is ”run.” The process leads to output distributions from which statistics such as minimums, maximums, means, and medians can be obtained.

Conceptually, the outbreak can be considered in two phases. First, prior to the first reporting of FMD (pre-detection phase), the disease can readily spread with the normal pattern of animal movements and other forms of interaction within the region. Second, once the disease has been confirmed, a control and eradication program is initiated (post-detection phase) and disease spread will be hampered by, for example, restrictions on the movement of livestock and reductions in inter-farm contact, by the identification and slaughter of affected herds, and by a vaccination strategy. AusSpread stores information about exposure events, infection events, and control and surveillance events on individual farms and provides summary outputs on a daily basis. The model also includes a module that tracks samples collected for laboratory testing and estimates the direct control costs and compensation payments. Outputs are provided in the form of tables, graphs, and maps.

2.2.2 Survey data collection

The data collection and survey analysis component was led by Dr. Bo Norby at Texas

A&M University. Using in-person interviews, data was collected from feedlots, beef herds, dairies, and swine operations. Data collection included size of operation, animal movements, contacts between different herd types, and seasonal variation in contacts and movements.

2.2.3 AusSpread Model Assumptions

Based on the survey data, assumptions 1-4 were made for the AusSpread model.

Assumption 1 - Direct and Indirect Contacts

The contacts determined for each premises could be divided into those leaving the premises, those coming to the premises, and indirect contacts. For direct contact, the percentage of animals from/to each possible contact premises was determined. The number of days per month for each contact premises and the number of locations per day were also ascertained. The direct-contact rate per month was determined for each premises, contact type, and contact premises combination by multiplying the number of days per month animals were moved by the number of locations per day. The numbers of people and vehicles that visited premises each month were determined, as was the number of premises that employees visited; this served as the indirect contact rate per month. Monthly contact rates were converted to daily contact rates by dividing monthly contact rates by 30. The number of times that animals came from or were sent out of state was determined, as were the state(s) involved. The frequency of horses and custom crews being used on premises was also determined. Semen shipments were determined for dairies. For all livestock types, the distances that animals and employees traveled between contacts were established. The values shown in Table 1 were used for daily direct and indirect contacts by herd type.

Table 1: Direct and Indirect Contact Rates by Herd Type

Farm	Type	Description	Contacts	DContacts	IContacts	PIDC	PIIC
1	feedlot1	Company owned feedlot (>50,000 head)	45	0	45	0.95	0.2
2	feedlot2	Stockholder feedlot (>20,000 but less than 50,000)	33	0	33	.95	.2
3	feedlot3	Custom feedlot (>5,000 but less than 20,000)	23	0	23	.95	.2
4	feedlot4	Backgrounder feedlot	6	1	5	0.95	0.2
5	feedlot5	Yearling-pasture feedlot	6	1	5	0.95	.2
6	feedlot6	Dairy Calf-raiser feedlot	6	1	5	0.95	0.2
7	small beef	<100 cattle	3.01	0.01	3	0.95	0.1
8	large beef	> 100 cattle	5.1	0.1	5	0.95	0.1
9	small dairy	<1000 number dairy cows	10.01	0.01	10	0.95	0.2
10	large dairy	>1000 number dairy cows	20.1	0.1	20	0.95	0.2
11	backyard	<10 cattle	5.01	0.01	5	0.9	0.15
12	small ruminant	sheep and goats	5.1	0.1	5	0.9	0.17
13	swine pig	concentrated animal feeding operations	11	1	10	1	1

key:Contacts = total number of contacts per day that could possibly result in transmission of FMD virus between herds
DContact (direct contacts) = total number of direct contacts per day; a direct contact was essentially the movement of livestock between herds e.g. direct contact of 0.10 for large dairies implies that, on average, a cow/calf is introduced every 10 days.
IContact (indirect contacts) = total number of indirect contacts per day; indirect contacts are all those contacts between herds that could transmit FMD virus, other than livestock movements. We assumed that people or equipment (such as vehicles and veterinary and husbandry equipment e.g. ropes, needles) contaminated with FMD virus from an infected herd would be an indirect contact if they potentially come in contact with livestock or where livestock are kept.
PIDC = probability of infection given a direct contact PIIC = probability of infection given an indirect contact
Once disease has been detected (day 7 or day 14, depending whether disease detection is assumed to be early or late) the number of direct contacts was reduced by 80%; the number of indirect contacts was reduced by 50%

Assumption 2 - Saleyards

Based on the survey data, the estimated number of buyers per sale was assumed to be 100. It was assumed that 90% of sales were in-region, with 10% being out-of-region. In-region buyers were assumed to travel to the sale a minimum of 10 km and a maximum of 150 km. The probability of sending livestock to sale was assumed to be 20%, and only herd types 7 and 8 (small and large beef) were assumed to sell livestock at sales. The probability of buying livestock from a sale was assumed to be 20%. Herd types 1-6, 7, 8, and 11 (company owned, stockholder, custom feedlot, backgrounder, yearling-pasture, dairy calf-raiser, small beef, large beef, large dairy, and backyard, respectively) were eligible to purchase from a sale. A saleyard was assumed to be infected if animals from an infected herd were sent to sale. The saleyard was reset to uninfected status after each sale. All saleyards were assumed to be shut down on day 8 or day 15 (depending upon whether early or late detection was simulated) following an incursion of FMD (1 day post-detection).

Assumption 3 - Airborne Spread

Airborne spread was assumed to be only possible from herd type 1 (company-owned feedlot) and herd type 13 (swine facility). The probability of airborne spread was dependent on temperature and humidity, and infection of herds depended on prevailing wind speed and direction. Average monthly climatic parameters were derived from the climatic data center weather station readings. The following assumptions were made for the proposed identification of high-risk areas.

The following assumption were made for the proposal of identifying high risk area.

Assumption 4 - The Best Mitigation Strategy Will Be Applied

According to the High Plains Project Report from the FAZD Center, the best mitigation strategy for epidemic length and number of herds is slaughter of infected animals, regular surveillance, early detection, ring vaccination, and adequate vaccination.

Assumption 5 -Selected Initiation Points (Index Herds) and Runs

Single-site incursions at a large feedlot, small feedlot, large beef, and backyard herd were used to initiate the epidemic for best mitigation strategy. For each simulation, at least 100 runs were required. For the simulation experiment, the total sample (N) is n by r; the type of randomization is complete randomized design (CRD); the type of the factors type of herds (T) is random; experimental units (EU) is measurement units (MU), which is EU = MU = individual simulation run; and the sources of variation is the types of herds and stochastic simulation runs.

2.3 Spatial Regression Analysis and Prediction

In epidemiologic research, there are two approaches, logistic regression and Poisson regression, that are widely used to model count outcomes.

2.3.1 Poisson Regression

Suppose that we observe binary outcomes $y_{i,k}$ from an Ausspread similation model, where $y_{i,k}$= 1 indicates the presence of the FMD disease in premises i and the kth run given a fixed start point, saying that S(0), {k=1,2...100}and $y_{i,k} = 0$ denotes its absence. Let π denote the (unknown) probability of disease prevalence in the population under study. The

random variable $y_{i,k}$ follows a Bernoulli distribution with a probability of disease π. The joint probability associated with the observed data $y_{1,k}, ..., y_{n,k}$ is

$$\begin{aligned} f(y_{1,k}, ..., y_{n,k}; \pi) &= \prod_{i=1}^{n} \pi^{y_{i,k}} (1-\pi)^{1-y_{i,k}} \\ &= exp[\sum_{i=1}^{n} log(1-\pi) + \sum_{i=1}^{n} y_{i,k} log(\frac{\pi}{1-\pi})] \end{aligned} \tag{2.1}$$

Here, $E(y_{i,k}) = \pi$, the canonical link is $g(E(y_{i,k})) = g(\pi) = log[\pi/(1-\pi)]$, known as the logit link. Logistic regression represents the GLM based on a Bernoulli random component and the logit link; that is, for covariates $x_1, ..., x_p$

$$\begin{aligned} log[\frac{\pi}{1-\pi}] &= \beta_0 + \beta_1 x_1 + ... + \beta_p x_p \\ &= X\beta \end{aligned} \tag{2.2}$$

A Poisson approximation of the binomial distribution is often used in modeling count data when n is large and $n\pi$ is small-for example, for a rare disease. The Poisson distribution also arises from modeling observed point locations as random events. A Poisson regression approach models the expected value as a function of regional covariates:

$$\begin{aligned} log[E(Y_i)] &= X\beta \\ E(Y_i) &= exp(X\beta) \end{aligned} \tag{2.3}$$

In equation 2.3, $Y_i = \sum_k^{100} y_{i,k}$ is the number of FMD disease samples present from 100 random simulations in the ith premises given start point S(0). X is a vector including $Dis_{0,i}$, the distance between the start point, S(0),, and the ith premises, and cattle number CN_i for the ith premises. Further, assume that the count results are a linear combination of

polynomial functions of the distance variable with degree r. That is,

$$\begin{aligned} log[E(Y_i)] &= X\beta \\ &= \gamma CN_i + \sum_r \beta_i Dis_{0,i}^r \end{aligned} \tag{2.4}$$

where degree r can be determined by corrected Akaike information criterion (AICc) and Bayesian information criterion(BIC) including here

1. Corrected Akaike Information Criterion

AICc=$k\frac{2n}{(n-k-1)}$-2ln(likelihood)

2. Bayesian Information Criterion ,

BIC=kln(N)-2ln(likelihood)

where k is the number of parameters and N is the number of observations.

2.3.2 Overdispersion

It has long been recognized that the Poisson distributional assumption imposes restrictions on the conditional moments of y that are often violated in applications. The most important of these is equality of the conditional variance and mean:

$$E(Y_i|x) = Var(Y_i|x)$$

A weaker assumption allows the variance-mean ratio to be any positive constant

$$E(Y_i|x) = \sigma^2 Var(Y_i|x)$$

When $\sigma^2 > 1$ it implies that the variance is greater than the mean; This situation is called overdispersion, and thus the standard error estimated from this model will be low (Waller and Gotway, 2004).

In the poisson regression model, the variance of the data depends on the mean, and thus the variance-covariance matrix of the data Y is

$$\Sigma = var(Y) = \sigma^2 V_\mu \tag{2.5}$$

where V_μ is an $N \times N$ diagonal matrix with the variance function terms on the diagonal, and the parameter σ^2 allowing for "inexactness" in the variance-to-mean relationships called overdispersion. The variance-covariance matrix defined in equation (2.5) is a generalization of the variance-covariance matrix assumed for linear regression models with uncorrelated residuals (Waller and Gotway, 2004). This model can be written as

$$log(Y) = X\beta$$

with

$$var(Y) = \sigma^2 V_\mu \tag{2.6}$$

2.3.3 Parameter Estimation

In general, this model with adjustment for overdispersion, can be written as

$$log(Y) = X\beta$$

with

$$var(Y) = \sigma^2 V_\mu \tag{2.7}$$

Wolfinger and O'Connell (1993)(Wolfinger and O'Connell, 1993) suggest an approach termed pseudolikelihood (PL) as a flexible and efficient way of estimating the unknown parameters in a generalized linear mixed model (GLMM). The procedure was described as follows

1. *Obtain a starting estimate of* β*, say* $\hat{\beta}$.
2. *Compute residuals* $r = Y - X\hat{\beta}$.
3. *Estimate the correspondingly,* $\Sigma_{\hat{a}}$
4. *Obtain a new estimate of* β *using*
   $\beta = \hat{\beta}_{gls} = (X'\Sigma_{\hat{a}}^{-1}X)^{-1}X'\Sigma_{\hat{a}}^{-1}Y$.
5. *Repeat steps 2-4 until* $|\hat{\beta}_n - \hat{\beta}_{n-1}| < \epsilon_\beta$ *and* $|\hat{a}_n - \hat{a}_{n-1}| < \epsilon_a$

2.3.4 Spatial Prediction

After the parameters are estimated, we can assume any premises as a start point and predict the number of events for other premises by the estimated parameters. Next, repeat this procedure until all premises have been used as the start point once. Finally, count and sum all prediction results and calculate the mean for each premises. In other words, this way seems like we mimic simulations according to existing results of the Ausspead model using all premises as the start point, then count the number of FMDs present for each. The following is the procedure:

- Order premises by ID number from the smallest to the largest, number it 1...n.
- Assume premises 1 as the start point, and compute the distance between premises 1 and the rest of the premises.
- Predict the probability of being infected when FMD disease is introduced into premises

1 for all premises using the equation

$$\hat{y}_{1,i} = exp(\gamma CN_i + \sum_r \beta_i Dis^r_{1,i})$$

where $Dis_{1,i}$ is the distance between the 1st start point and the ith premises and CN_i is the cattle number in i^{th} premises.

- Select premises 2 as the start point, repeat the procedure, then premises 3 until premise n;
- Compute the expected number of each premises'disease present by the equation:

$$E\hat{y}_i = \bar{\hat{y}}_{j,i} = \frac{1}{n}\sum_{j=1}^{n} \hat{y}_{j,i}$$

2.4 Procedure

Data from the AUSSPREAD simulation model were used in this phase, in which there were 100 runs under each scenario. Across the 100 random trials, the number of events for each premises was counted using the SAS SQL function. The count outcome was then used as the dependent variable in a Poisson regression with adjustment for overdispersion. The independent variables were then

- The number of animal in each premises'acreage.
- Distance of the premises' from the disease initiation point calculated based on longitudes (x) and latitudes (y) via the Euclidean distance equation:
  $dis_{0,i} = \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2}$.
  where x and y are coordinators.

We selected four different scenarios: an FMD disease introduced from large feedlots, small feedlots, large beef, and backyard. For each scenario, we used a spatial regression model to estimate the parameters of the model given one location as the start point, then, ac-

cording to the estimated parameters, we predicted the probability/risk of an FMD outbreak spreading to the premises given others as the start points in the study area.

2.4.1 Scenario 1

2.4.1.1 Parameter Estimation

In scenario 1, we assume that an FMD virus is introduced in large feedlots. We used a Poisson regression model with adjustment for dispersion to determine the polynomial degree r. Table 2 summarizes the estimation results for that parameter and shows fits obtained via AICc and BIC for r values from 1 to 3. Table 2 shows that r = 3 with minimum AICc, and BIC exhibits significantly better fit than that (r = 1 and r = 3). The dispersion parameter was estimated as 7.9280, with a standard error of 0.1516, significantly different from one, implying overdispersion. Thus, this model can be written as:

$$log[E(Y_i)] = 3.7326 + 0.008184CN_i - 0.2324Dis_{0,i} + 0.00623Dis_{0,i}^2 - 0.00005Dis_{0,i}^3$$

with

$$var(Y|X) = 7.9280V_\mu \tag{2.8}$$

From Table 2, as we expected, animal number has a significant positive impact on the possibility of an outbreak reaching a premises. The estimated parameter is 0.00818, implying that when the animal number increases by 1,000 the probability of being infected will increase 0.35%. The distance from the start point has a negative impact. The relationship between distance and outbreak probability for a single premises, keeping animal density constant, is plotted in panel 1 of Fig. 2. The figure indicates that distance has a larger negative impact on the number of events when distance is shorter (absolute value of slope is large), while this impact is tiny when distance is more than 20 miles (absolute value of slope is close to zero).

Table 2: Parameter Estimation under Scenario 1

	r=1		r=2		r=3	
Parameters	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Intercept	1.9961	0.04796	2.7040	0.0608	3.7326	0.07341
CN	0.01761	0.00532	0.0152	0.0045	0.0081	0.00412
Dis	-0.01958	0.00140	-0.0749	0.0039	-0.2324	0.0093
Dis^2			0.0008	0.00005	0.0062	0.00031
Dis^3					-0.00005	2.96E-06
Dispersion(σ^2)	10.6908		8.4344		7.9280	
SD of σ^2	0.2044		0.1613		0.1516	
AICc	**21356.4**		**20212.4**		**20064.2**	
BIC	**21363.1**		**20219.0**		**20070.8**	
Observations	5474		5474		5474	

Note: CN is cattle number in each premises.

Dis is the distance between the premises and the disease initiation point.

σ^2 is the dispersion parameter.

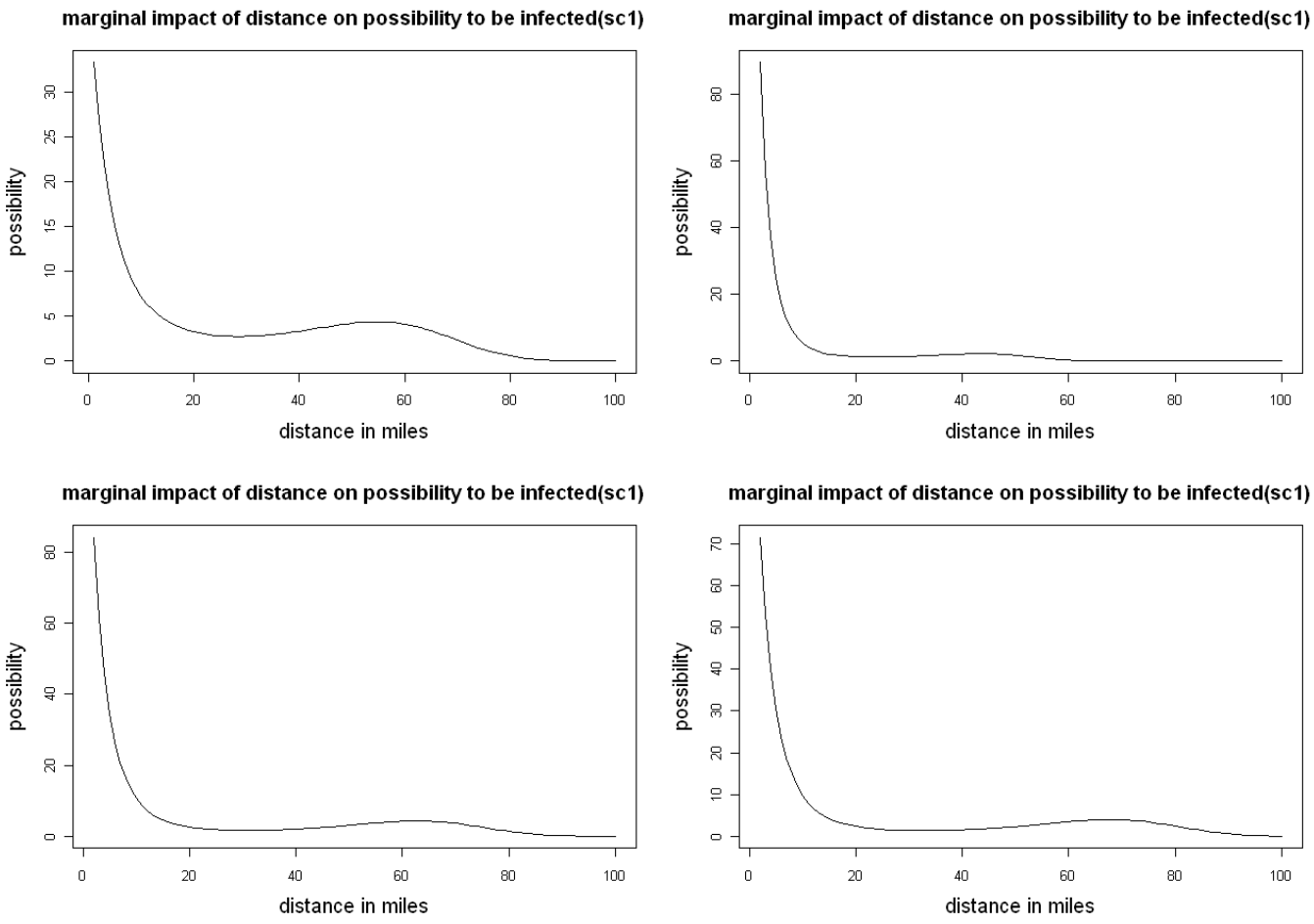


Figure 2: Estimated Distance Impact on Possibility of Disease Present

2.4.1.2 Prediction and Results

Using parameters estimated in Table 2, we select all 58 large feedlots as start points. For example, in those 58 large feedlots, when the jth large feedlot is selected as a start point, the number of ith premises' disease present can be predicted by the following procedure.

- Order large feedlots by ID number from the smallest to the largest, and number them 1...58.
- Select large feedlot 1 as a start point; compute the distance between large feedlot 1 and the rest of the premises.
- Predict the probability of being infected when FMD disease is introduced into large feedlot 1 for all premises by the equation

  $\hat{y}_{j,i} = exp(3.7326 + 0.008184CN_i - 0.2324Dis_{j,i} + 0.00623Dis_{j,i}^2 - 0.00005Dis_{j,i}^3)$

  where $Dis_{1,i}$ is distance between 1st start point and i^{th} premise and CN_i is cattle number in i^{th} premise.
- Select large feedlots 2 as start point, repeat the procedure, then large feedlots 3 till large feedlots 58;
- Compute the expected number of each premise disease present by equation:

  $$E\hat{y}_i = \bar{\hat{y}}_{j,i} = \frac{1}{n}\sum_{j=1}^{n}\hat{y}_{j,i}$$

  where n=58.

The predicted results are mapped and presented in Fig. 3. For easier reading of the results, we transformed the discrete points into a continuous surface by the ordinary Kringing interpolation technique. Dark brown represents higher probability, while light yellow represents lower probability. According to the map, the southeast of Deaf Smith and the west

of Castro County have approximately a 10% possibility of presenting disease when one FMD virus is randomly introduced into large feedlots in the study area, while other areas are predicted to have lower probabilities. For example, most areas of Randall county are estimated to have approximately a 2-3% possibility of presenting disease. Since the cattle number plays a critical role in expected animal loss, the expected animal loss provides a different picture, which is computed by

$$ECL_i = \hat{y}_i \times CN_i \text{and}$$

$$TECL_i = \sum_i^n ECL_i$$

Figure 4 shows the high loss area in Castro, Pamper, and Deaf Smith Counties because of the large feedlots concentrated in those three counties. The total estimated expected cattle loss is more than 141,000 under scenario 1, in which an FMD virus is randomly introduced into large feedlots.

2.4.2 Scenario 2

2.4.2.1 Parameter Estimation

In scenario 2, we assume that an FMD virus is introduced in small feedlots. We used a Poisson regression model with adjustment for dispersion to determine the polynomial degree r. Table 3 summarizes the estimation results for that parameter and shows fits obtained via AICc and BIC for r values from 1 to 3. Table 3 shows that r = 3 with minimum AICc, and that BIC exhibits significantly better fit than that of r = 1 and r = 2. The dispersion parameter was estimated as 1.4760, with a standard error of 0.03072, which is significantly different from one, implying slight overdispersion. Thus, this model can be written as:

$$log[E(Y_i)] = 5.5067 + 0.00675CN_i - 0.5391Dis_{0,i} + 0.01730Dis_{0,i}^2 - 0.00017Dis_{0,i}^3$$

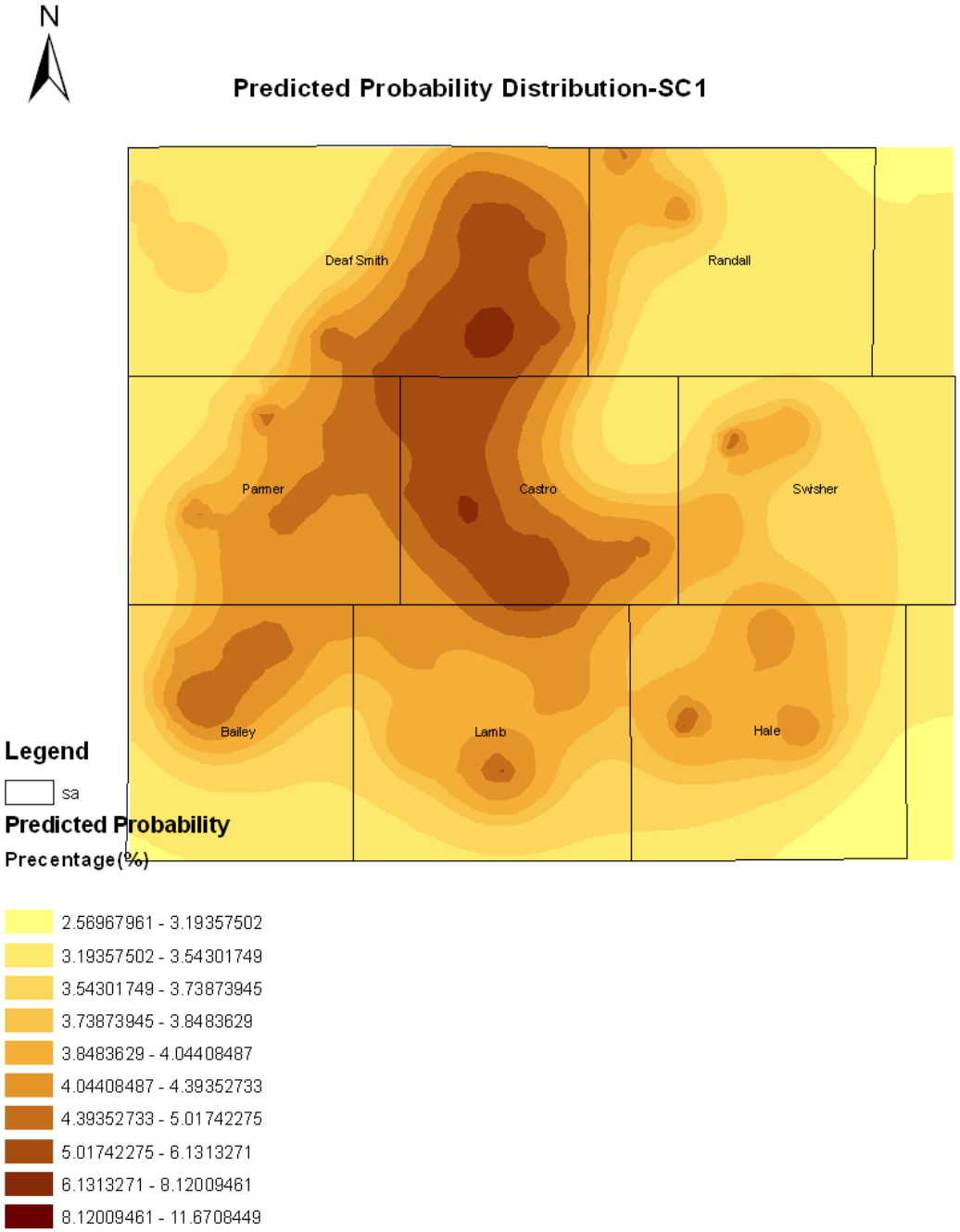


Figure 3: Predicted Probability Distribution under Scenario 1

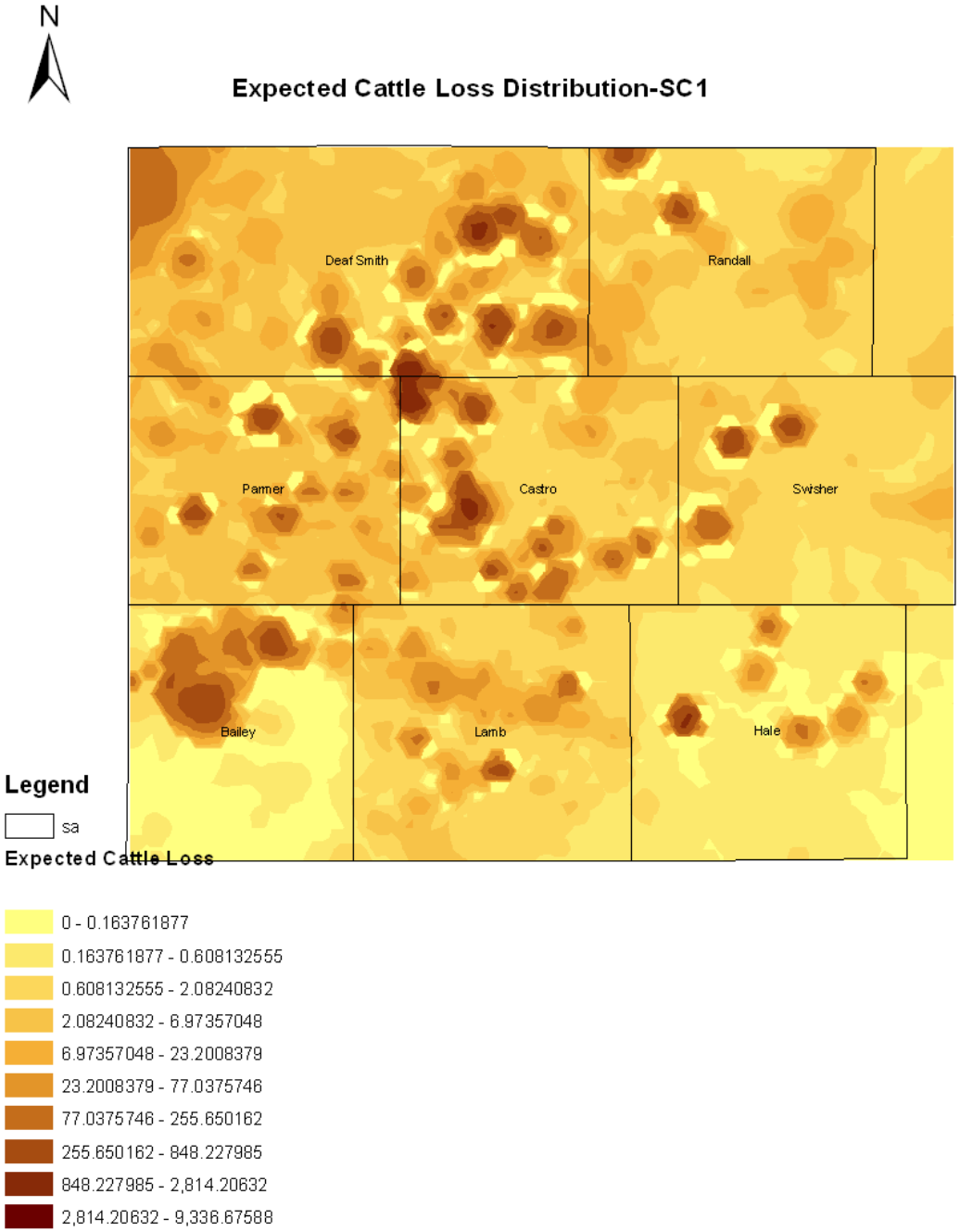


Figure 4: The Expected Cattle Loss Distribution under Scenario 1

Table 3: Parameter Estimation under Scenario 2

	r=1		r=2		r=3	
Parameters	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Intercept	3.6479	0.04065	4.6665	0.02422	5.5067	0.02153
CN	0.000148	0.006907	0.002260	0.004443	0.00675	0.003199
Dis	-0.1028	0.001988	-0.2569	0.0024621	-0.5391	0.005574
Dis^2			0.003537	0.000045	0.01730	0.000263
Dis^3					-0.00017	3.298E-6
Dispersion(σ^2)	6.9599		2.5777		1.4760	
SD of σ^2	0.1448		0.05364		0.03072	
AICc	**19441.2**		**14773.9**		**11976.3**	
BIC	**19447.6**		**14780.4**		**11982.7**	
Observations	4623		4623		4623	

Note: CN is cattle number in each premises.
Dis is the distance between the premises and the disease initiation point.
σ^2 is the dispersion parameter.

with

$$var(Y|X) = 1.4760V_\mu \tag{2.9}$$

From Table 3, as we expected, animal number has a significant positive impact on the possibility of an outbreak reaching a premises. The estimated parameter is 0.00675, implying that when the animal number increases by 1,000 the probability will increase with an exponential function with cattle number, exp(0.00675*CN). The distance from the start point has a negative impact. The relationship between distance and outbreak probability for a single premises, keeping animal density constant, is plotted in panel 2 of Fig. 2, which indicates that distance has a larger negative impact on the number of events when distance is shorter, while this impact is tiny when distance is more than 20 miles.

2.4.2.2 Prediction and Results

Similarly, using parameters estimated in Table 3, we select all 26 small feedlots as start points. The predicted results from a similar procedure were mapped and presented

in Fig. 5. According to the map, the southeast of Deaf Smith County and the southwest of Castro County represent a little over 10% possibility of presenting disease when one FMD virus is randomly introduced into small feedlots in the study area, while other areas are predicted to have lower probabilities. For example, most areas of Hale County are estimated to have approximately a 1-2% possibility of presenting disease. Figure 6 shows the high-cattle-loss area in Deaf Smith and the western part of Castro County. Again, a total estimated expected cattle loss is more than 137,000 under scenario 2, with an FMD virus randomly introduced into small feedlots, which is slightly lower than under scenario 1.

2.4.3 Scenario 3

2.4.3.1 Parameter Estimation

In scenario 3, we assume that an FMD virus is introduced in large beef. Table 4 summarizes the estimation results for that parameter and shows fits obtained via AICc and BIC for r values from 1 to 3. Table 4 shows that r = 3 with minimum AICc and BIC exhibits significantly better fit than that of r = 1 and r = 2. The dispersion parameter was estimated as 1.0341, with a standard error of 0.02930, which is insignificantly different from one, implying no dispersion. Thus, this model can be written as:

$$log[E(Y_i)] = 5.1048 + 0.0127CN_i - 0.3523Dis_{0,i} + 0.008453Dis_{0,i}^2 - 0.00006Dis_{0,i}^3$$

with

$$var(Y|X) = 1.0341V_\mu \tag{2.10}$$

From Table 4, as we expected, animal number has a significant positive impact on the possibility of an outbreak reaching a premises. The estimated parameter is 0.0127, implying that when the animal number increases by 1,000 the probability will increase by

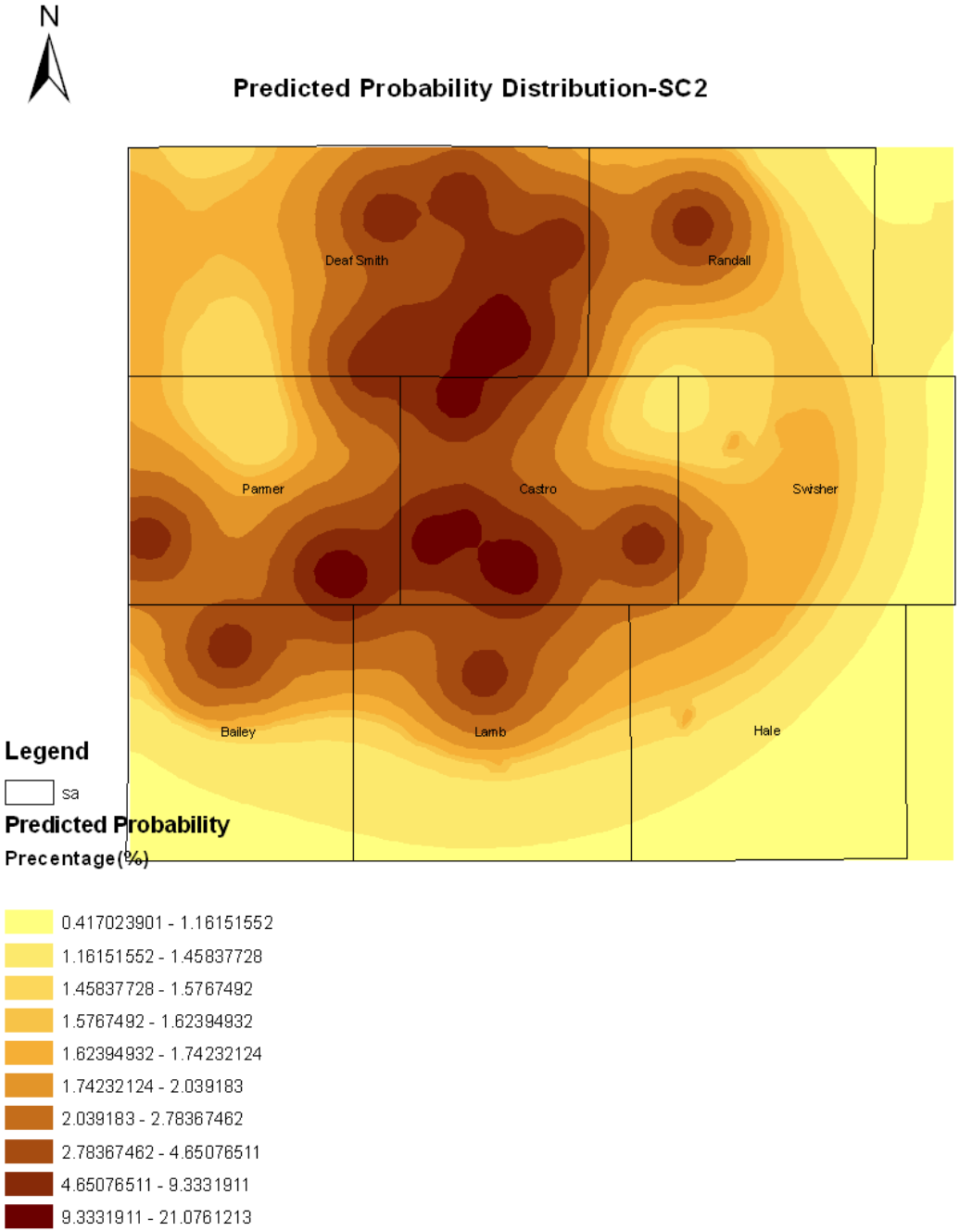


Figure 5: Predicted Probability Distribution under Scenario 2

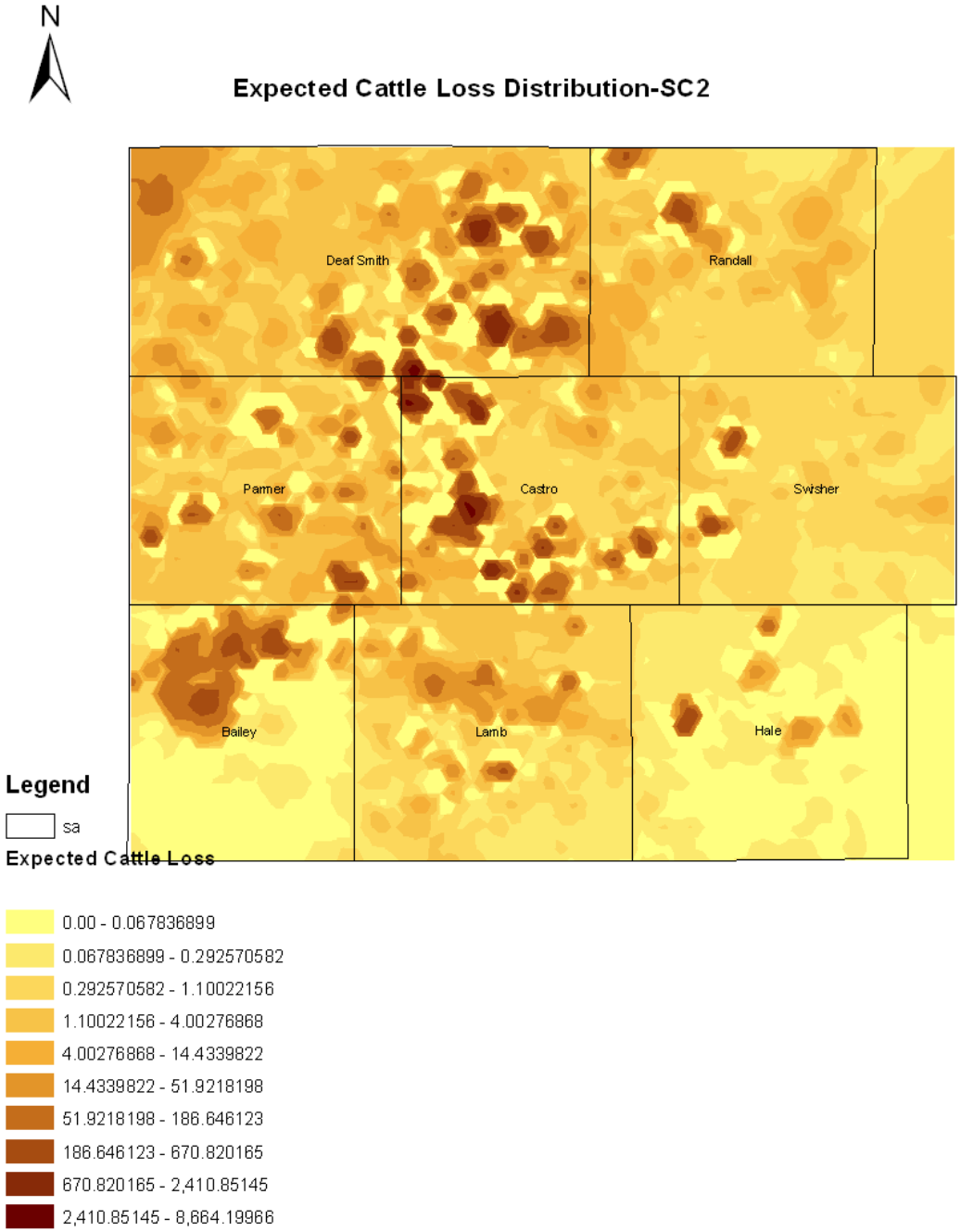


Figure 6: The Expected Cattle Loss Distribution under Scenario 2

Table 4: Parameter Estimation under Scenario 3

	r=1		r=2		r=3	
Parameters	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Intercept	2.7757	0.05843	4.0823	0.04352	5.1048	0.03458
CN	0.003134	0.005387	0.008719	0.003709	0.0127	0.002795
Dis	-0.05114	0.001744	-0.1501	0.002670	-0.3523	0.005057
Dis^2			0.001379	0.000033	0.008453	0.000170
Dis^3					-0.00006	1.546E-6
Dispersion(σ^2)	3.8852		1.8788		1.0341	
SD of σ^2	0.1100		0.05323		0.02930	
AICc	**9051.0**		**7210.8**		**5786.7**	
BIC	**9056.9**		**7216.6**		**5792.5**	
Observations	2496		2496		2496	

Note: CN is cattle number in each premises.
Dis is the distance between the premises and the disease initiation point.
σ^2 is the dispersion parameter.

an exponential function with cattle number, exp(0.0127*CN). The distance from the start point has a negative impact. The relationship between distance and outbreak probability for a single premises, keeping animal density constant, is plotted in panel 3 of Fig. 2, which indicates that distance has a larger negative impact on the number of events when distance is shorter, while this impact is tiny when distance is more than 20 miles.

2.4.3.2 Prediction and Results

Similarly, using the parameters estimated in Table 4, we select all 740 large beef as start points. The predicted results from a similar procedure were mapped and presented in Fig. 7. According to the map, the high-risk areas concentrate in Parmer County, with an 8-10 % possibility of presenting disease when one FMD virus is randomly introduced into large beef in the study area, while other areas are predicted to have lower probabilities; for example, most areas of Bailey, Castro, and Hale Counties are estimated to have approximately a 1-2% possibility of presenting disease. Figure 8 shows the high cattle loss area

in Deaf Smith, Parmer, and the west of Castro County. Again, a total estimated expected cattle loss is more than 150,000 under scenario 3, with an FMD virus randomly introduced into large beef, which is slightly lower than those under scenarios 1 and 2.

2.4.4 Scenario 4

2.4.4.1 Parameter Estimation

In scenario 4, we assume that an FMD virus is introduced in backyard. Table 5 summarizes the estimation results for that parameter and shows fits obtained via AICc and BIC for r values from 1 to 3. Table 5 shows that r = 3 with minimum AICc and BIC exhibits significantly better fit than that of r = 1 and r = 2. The dispersion parameter was estimated as 1.0341, with a standard error of 0.02930, which is significantly less than one, implying underdispersion. Thus, this model can be written as:

$$log[E(Y_i)] = 4.8847 + 0.00217CN_i - 0.3306Dis_{0,i} + 0.007472Dis_{0,i}^2 - 0.00005Dis_{0,i}^3$$

with

$$var(Y|X) = 0.8893V_\mu \tag{2.11}$$

From Table 5, as we expected, animal number has a significant positive impact on the possibility of an outbreak reaching a premises. The estimated parameter is 0.00217, but it is insignificant. The distance from the start point has a negative impact. The relationship between distance and outbreak probability for a single premises, keeping animal density constant, is plotted in panel 4 of Fig. 2, which indicates that distance has a larger negative impact on the number of events when distance is shorter, while this impact is tiny when distance is more than 20 miles.

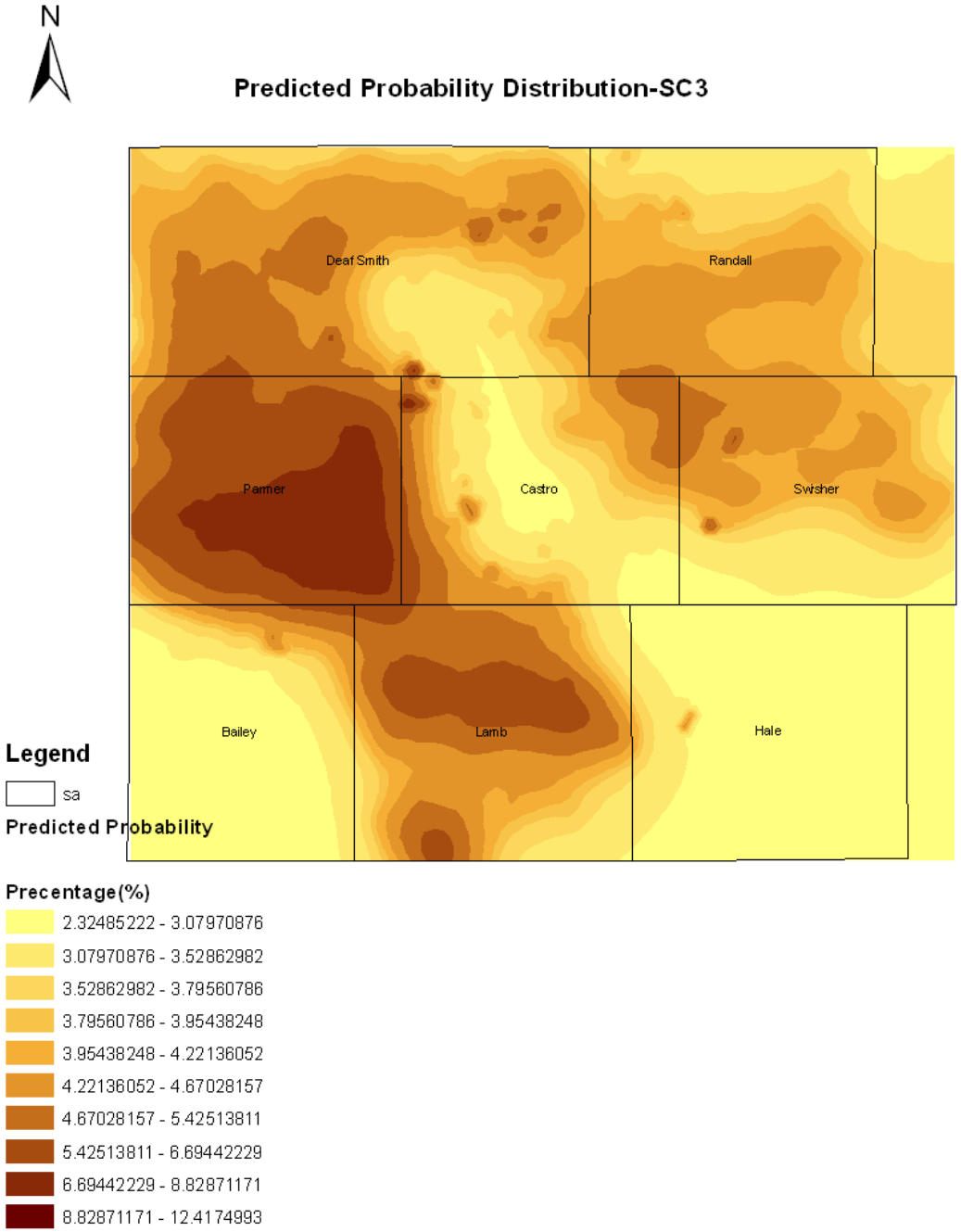


Figure 7: Predicted Probability Distribution under Scenario 3

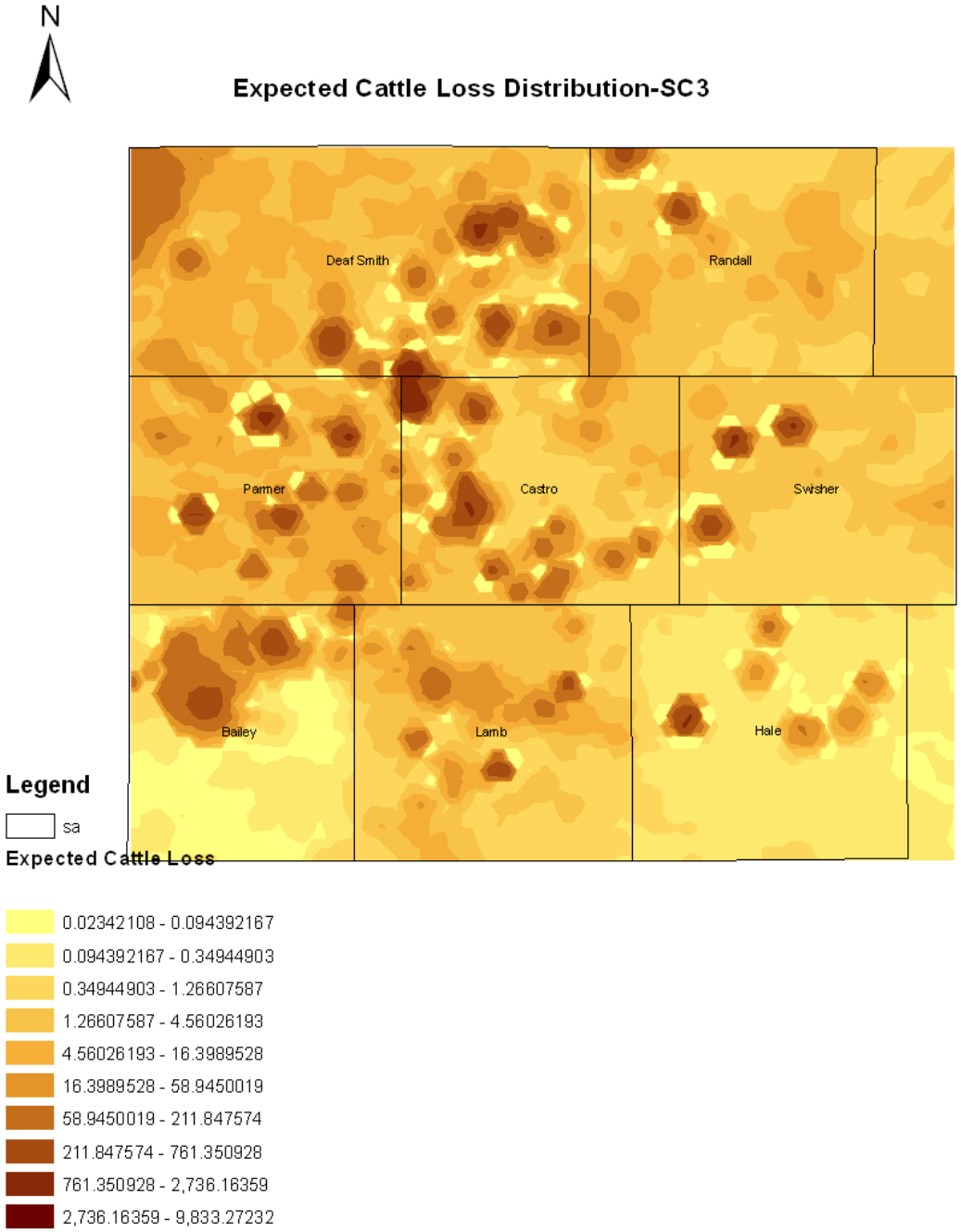


Figure 8: The Expected Cattle Loss Distribution under Scenario 3

Table 5: Parameter Estimation under Scenario 4

	r=1		r=2		r=3	
Parameters	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Intercept	2.8910	0.04301	4.1790	0.02851	4.8847	0.02289
CN	-0.01468	0.01317	0.002355	0.007721	0.002170	0.005806
Dis	-0.05425	0.001238	-0.1645	0.001908	-0.3306	0.003699
Dis^2			0.001559	0.000024	0.007472	0.000126
Dis^3					-0.00005	1.16E-6
Dispersion(σ^2)	3.6251		1.4614		0.8893	
SD of σ^2	0.08229		0.03318		0.02019	
AICc	**14676.4**		**11140.9**		**9045.0**	
BIC	**14682.6**		**11147.2**		**9051.3**	
Observations	3884		3884		3884	

Note: CN is cattle number in each premises.
Dis is the distance between the premises and the disease initiation point.
σ^2 is the dispersion parameter.

2.4.4.2 Prediction and Results

Similarly, using the parameters estimated in Table 5, we select all 620 backyards as start points. The predicted results from a similar procedure were mapped and presented in Fig. 9. According to the map, the high-risk areas are concentrated in Lamb and Swisher Counties, with a 5-7% possibility of presenting disease when one FMD virus is randomly introduced into backyards in the study area, while other areas are predicted with lower probability-for example, other counties are estimated to have approximately a 1-2% possibility of presenting disease. Figure 10 shows the high-cattle-loss area in Deaf Smith, Parmer, and the west of Castro County. Again, the total estimated expected cattle loss is more than 88,000 under scenario 4, with an FMD virus randomly introduced into large beef, which is much lower than those under scenarios 1-3.

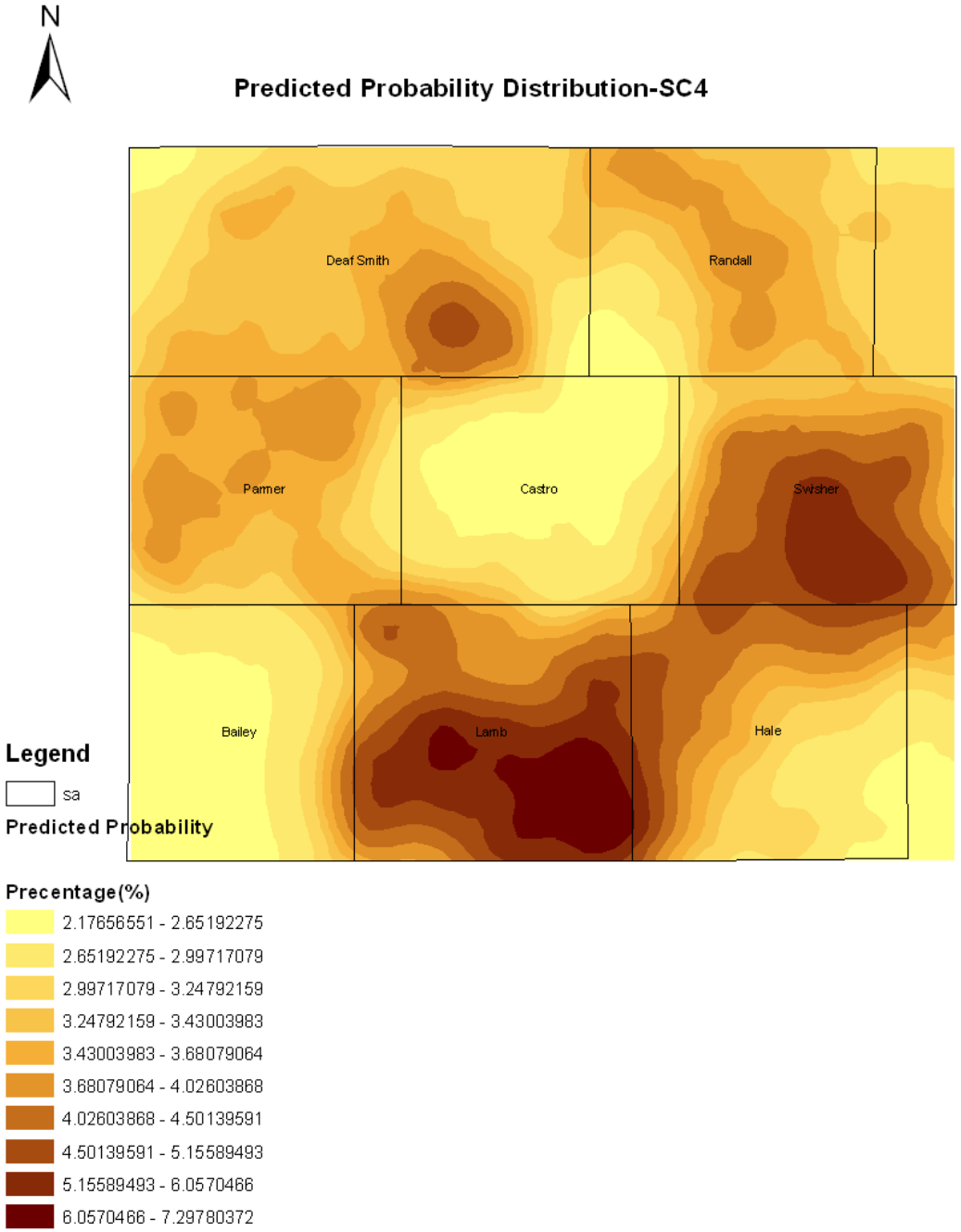


Figure 9: Predicted Probability Distribution under Scenario 4

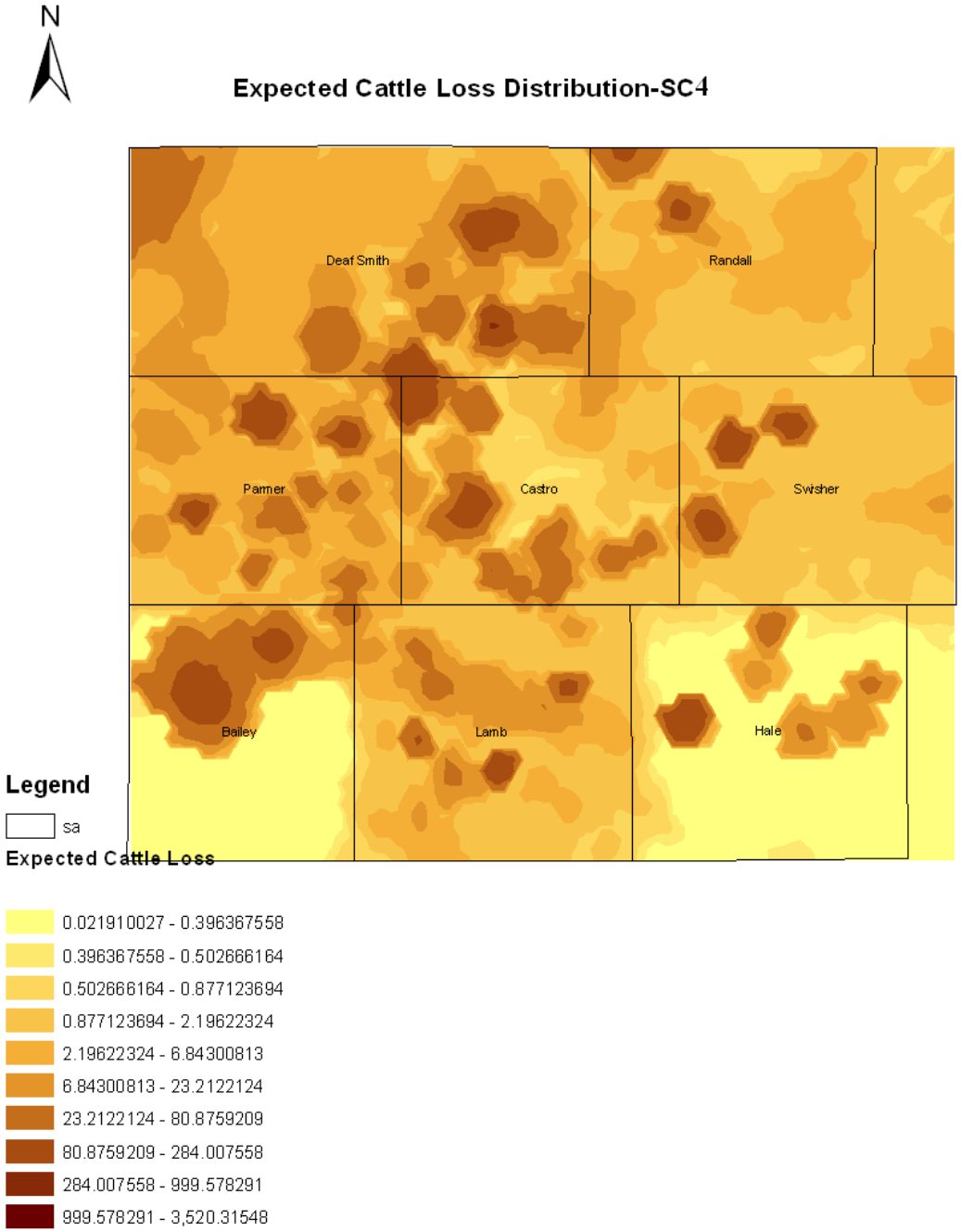


Figure 10: The Expected Animal Loss Distribution under Scenario 4

2.5 Summary

In this chapter, we use a Poisson regression model with adjustment dispersion associated with random simulation results from the AusSpead model to estimate the parameters of the model given one location as the start point in the simulation, and we predicted the probability/risk and expected cattle loss of an FMD outbreak spreading to the premises given others as start points under different scenarios in the study area.

Table 6 summarizes the estimated results under four different scenarios. Cattle numbers have a positive effect on the probability of being infected, while the distance between the start point and a given premises has a negative effect. Under different scenarios, the impact is slightly different. Because of the marginal impact of distance on probability in the Poisson model with a high-order polynomial function, it is difficult to obtain the marginal impact; we plot the relationship between distance and probability. Figure 2 shows that distance has a similar negative impact on the number of events under the four different scenarios. That is, when distance is shorter-while this impact is tiny when distance is more than 20 miles or when the premises are far from the start point (over 20 miles)-the impact is the same regardless of the distance. In other words, if the distance between a premises and an outbreak point is shorter than 20 miles, the ”marginal” impact of distance will steeply rise when distance decreases, while if the distance between a premises and the outbreak point is longer than 20 miles, an increase or decrease in distance will not impact the probability.

It is clear that because distance plays a important role in predicting event probability, as return, identifying high-risk areas depends on the spatial distributions of premises, and high density of premises usually has high probability of transmission of the virus or be-

coming infected. The total expected cattle loss plays an important role in decision making. When FMD hits large premises-for example, large feedlots or large beef-a large cattle loss will occur. Based on the AusSpead simulation model, our estimation and prediction show that large cattle loss is concentrated in three counties-Deaf Smith, Parmer, and Castro-those results are from approximately 70% feedlots with over 10,000 cattle located in the three counties. When an FMD virus is introduced into backyard, the expected loss is about 88,000 head, while when an FMD virus is introduced into large or small feedlots or large beef the losses are approximately double. They are 141, 137, and 150 thousand head, respectively.

Table 6: Summary of Parameter Estimation under Different Scenarios

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Parameters	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Intercept	3.7326	$< .0001$	5.5067	$< .0001$	5.1048	$< .0001$	4.9051	$< .0001$
CN	0.008184	.0475	0.006752	0.0348	0.0127	$< .0001$	0.002192	.70
Dis	-0.2324	$< .0001$	-0.5391	$< .0001$	-0.3523	$< .0001$	-0.333	$< .0001$
Dis^2	0.00623	$< .0001$	0.0173	$< .0001$	0.008453	$< .0001$	0.007538	$< .0001$
Dis^3	-0.00005	$< .0001$	-0.00017	$< .0001$	-0.00006	$< .0001$	-0.00005	$< .0001$
Dispersion(σ^2)	7.928		1.476		1.0341		0.8893	
SD of σ^2	0.1516		0.03072		0.02930		0.02019	
Observations	5474		4623		2496		3884	
Total cattle loss	141,033		137,728		150,021		88,407	

Note: CN is cattle number in each premises.

Dis is the distance between the premises and the disease initiation point.

σ^2 is the dispersion parameter.

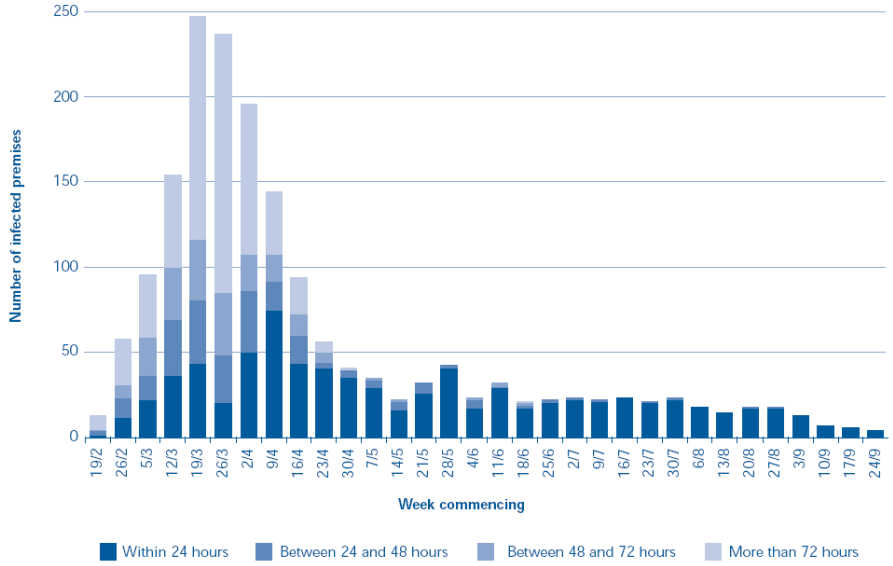
CHAPTER III

ANALYZING ANIMAL CARCASS DISPOSAL COSTS

3.1 Introduction

Foot and mouth disease is highly contagious and one of the most economically costly diseases affecting livestock. The 2001 FMD outbreak in the United Kingdom demonstrated the need for effective disease control and eradication strategies and carcass disposal to minimize event costs. Various methods are possible, and preplanning should consider these methods based on their potential feasibility and cost effectiveness. A potential major outbreak of FMD in the United States would involve mass slaughter and disposal of animal carcasses because U.S. livestock are completely susceptible to this disease. Whether at the hand of accidental disease entry, typical animal-production mortality, natural disaster, or an act of terrorism, livestock deaths pose daunting carcass-disposal challenges. Effective means of carcass disposal are perhaps most crucial for disease eradication efforts. Rapid slaughter and disposal of livestock are integral parts of effective disease eradication strategies.

During 2001 U.K. FMD outbreak, more than six million animals were slaughtered: over four million for disease control purposes, and over two million for welfare reasons. The sheer scale of the epidemic made disposal a critical problem. On infected premises, disposal speeds were particularly slow until the third week of April 2001, when, for the first time, disposal was completed on more than half of infected premises within 24 hours of slaughter (Fig. 11). Until then, the daily totals for slaughtering had run ahead of disposals.



NOTE

The elapsed times shown are those between the slaughter of the last susceptible animal and disposal of the last animal.

Source: National Audit Office analysis of the records of 1,836 infected premises for which clear information was available on time between slaughter and disposal. The data was extracted from the Department's Disease Control System.

Figure 11: Elapsed Time between Completion of Slaughter and Disposal for Infected Premises during the 2001 Outbreak

On between a quarter and a third of infected premises, slaughtered animals were left lying on the ground for four days or more during these first seven weeks of the epidemic. As a result, the number of slaughtered animals awaiting disposal on infected premises increased rapidly, peaking at 140,000 on April 1, 2001 (Fig. 12). The number on dangerous contact premises peaked at 169,000 on April 14 (National Audit Office (NAO): The 2001 Outbreak of Foot and Mouth Disease).

The 2001 FMD outbreak in the U.K. resulted in carcass disposal costs of £ 3 billion (US$4.2 billion)to the government, of which carcass disposal cost was approximately £ 164 (US$230) million, or 5.5% of the total government cost of the outbreak (Fig. 13). During the 1997 FMD outbreak in Taiwan, when approximately 3.8 million animals were

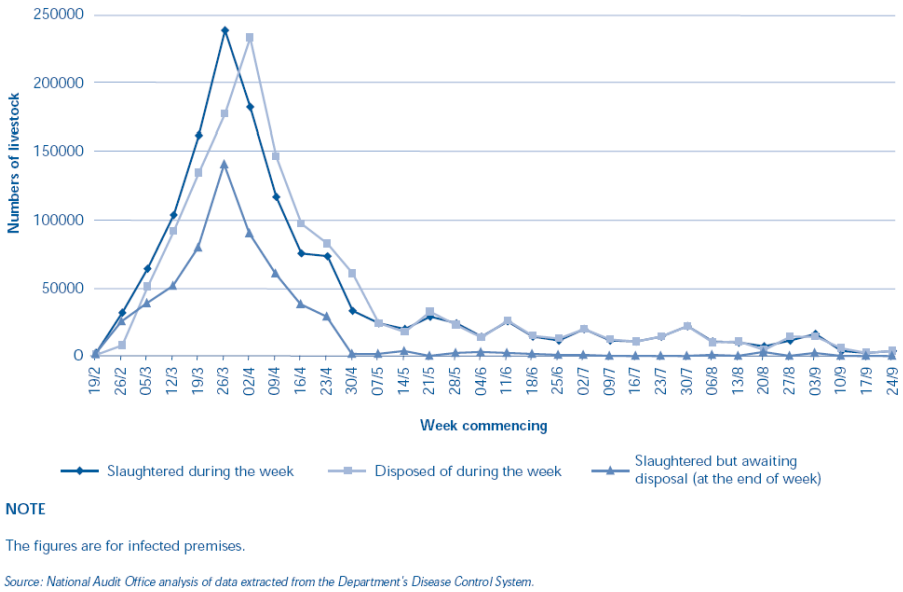


Figure 12: Animals Slaughtered, Disposed of and Awaiting Disposal by Week during the 2001 Outbreak

slaughtered and disposed of, the costs borne by the government associated with the epidemic were estimated at US$187.5 million, with carcass disposal costing approximately $24.6 million, or about 13% of total government cost.

Realization of a rapid response requires emergency management plans that are rooted in a thorough understanding of disposal alternatives. Strategies for carcass disposal-especially large-scale carcass disposal-require preparation well in advance of an emergency in order to maximize the efficiency of response. The most effective disposal strategies will be those that exploit every available and suitable disposal option to the fullest extent possible, regardless of what those options might be. It may seem straightforward, or even tempting, to suggest a step-wise disposal option hierarchy outlining the most and least preferred methods of disposal. However, for a multi-dimensional enterprise such as carcass disposal, hierarchies may be of limited value because they are incapable of fully capturing and systematizing the relevant dimensions at stake (e.g., environmental considerations, disease

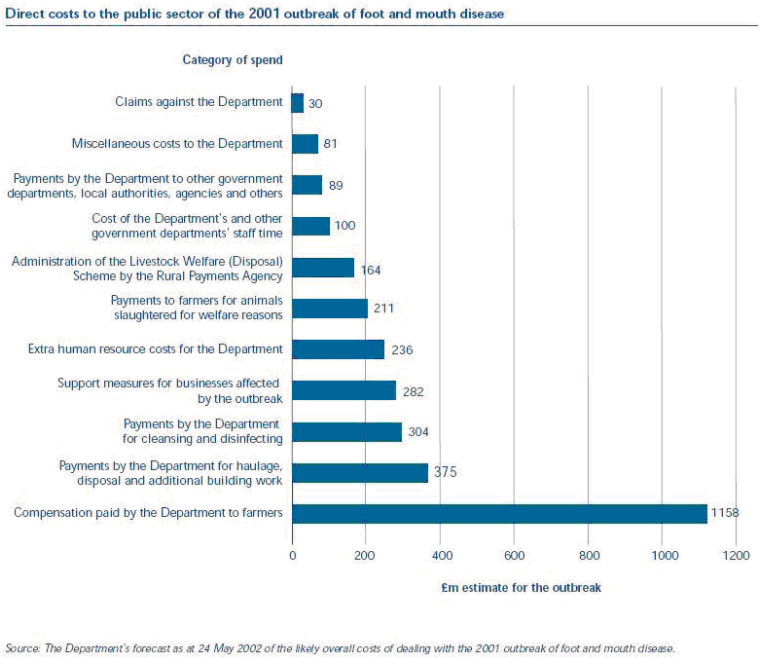


Figure 13: Direct Cost to the Public Sector of the 2001 Outbreak of FMD

agent considerations, availability of technology, cost, etc.). Even with a disposal-option hierarchy that, for example, ranks the most environmentally preferred disposal technologies for a particular disease, difficulties arise when the most preferred methods are not available or when capacity has been exhausted. In these situations, decision makers may have to consider the least preferred means. In such a scenario (one that is likely to occur in the midst of an emergency), there are tremendous benefits to being armed with a comprehensive understanding of an array of carcass-disposal technologies. Decision makers should come to understand each disposal technology available to them, thereby equipping themselves with a comprehensive toolkit of knowledge. Such awareness implies an understanding of an array of factors for each technology, including the principles of operation, logistical details, personnel requirements, likely costs, environmental considerations, disease agent considerations, advantages and disadvantages, and lessons learned for each technology. In the absence of a wealth of observable data on FMD outbreaks, disease modeling is the main

tool for predicting the likely spread of the disease and for evaluating the effectiveness of various mitigation strategies (Bates et al., 2003).

In this chapter, our aims are to determine the best mitigation strategies with average minimum animal loss and under the best strategy. We make preparation for the ”worst” status, estimating costs of disposing of animal carcasses and transportation following a largest FMD outbreak under four different scenarios, and we examine the effectiveness of disposal strategies. To achieve the goal, we test 15 mitigation strategies based on simulation results by multiple comparison and the best strategy group, then we select one of the best mitigation strategies for the four different scenarios and estimate minimum costs of disposing of animal carcasses and transportation.

3.2 Experimental Design and Test

3.2.1 Experimental Design Description

The data collected and the experimental design were described in Chapter I. Here, we only describe the fifteen mitigation strategies, which are provided in Table 7.

Table 7: Mitigation Strategy

Strategy	Description
1	Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, early detection
2	Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, late detection
3	Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, late detection, targeted vaccination, adequate vaccine
4	Ring slaughter, regular surveillance, slaughter of infecteds, slaughter of dc's, late detection, targeted vaccination, inadequate vaccine
5	Enhanced surveillance, slaughter of infecteds, slaughter of dc's, early detection
6	Enhanced surveillance, slaughter of infecteds, slaughter of dc's, late detection
7	Enhanced surveillance, slaughter of infecteds, slaughter of dc's, late detection,targeted vaccination, adequate vaccine
8	Enhanced surveillance, slaughter of infecteds, slaughter of dc's, late detection,targeted vaccination, inadequate vaccine
9	Slaughter of infecteds, slaughter of dc's, regular surveillance, ring vaccination,early detection, inadequate vaccine
10	Slaughter of infecteds, slaughter of dc's, regular surveillance, early detection
11	Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection, ring vaccination, adequate vaccine
12	Slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, targeted vaccination, adequate vaccine
13	Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection
14	Slaughter of infecteds, slaughter of dc's, regular surveillance, late detection, targeted vaccination, adequate vaccine
15	Slaughter of infecteds, slaughter of dc's, regular surveillance, early detection, ring vaccination, adequate vaccine

3.2.2 Test the Best Strategies

The number and type of animals lost were calculated according to herd status as generated by the AusSpread epidemic model, coupled with information on herd size. Herds with the status of infected, dead, immune, or latent were counted toward lost value. Losses by animal type were calculated by multiplying size by animal type distribution. This measure was summed for all herds slaughtered.

3.2.2.1 Scenario 1

In scenario 1, we assume that an FMD virus is introduced in large feedlots. Fifteen strategies were tested, and each strategy was given 100 runs, with all animal loss for each run being summed. A total of 100 observations were obtained. We used the Tukey test, probably the most conservative multiple-comparison test, controlled at a significance level of 5%. Table 8 provides the mean and standard deviation and test results. The groups with the same letter are insignificantly different. For example, strategies 7, 15, and 3, with average animal losses over 100 runs being 989,844; 977,007; and 917,307, respectively, have the same letter A, indicating that the three strategies cause insignificant differences in animal loss at the 5% level. Strategy 3 also has letter B, as with strategies 4 and 8, indicating that strategy 3 also is insignificantly different from strategies 4 and 8 in animal loss at 5%. But strategies 4 and 8 are indeed better than strategies 7 and 15, with significantly less animal loss. Overall, the best strategies are 15, 9, 1, 10, and 5, with the least animal loss (121,029; 117,262; 101,205; 97,374; and 96,105, respectively).

3.2.2.2 Scenario 2

In scenario 2, we assume that an FMD virus is introduced in small feedlots. Similar

Table 8: Multiple Comparison for Animal Loss under Scenario 1

Group		strategy	observations	Mean	Standard Deviation
	A	7	100	989844	312690.005
	A	15	100	977007	357182.846
B	A	3	100	917307	326094.017
B		4	100	862727	327190.377
B		8	100	831726	342778.246
	C	12	100	442401	225067.29
	D	11	100	231375	87213.237
E	D	6	100	178570	70821.63
E	D	13	100	170126	73038.509
E	D	2	100	166746	65413.011
E		15	100	121029	56677.659
E		9	100	117262	82946.118
E		1	100	101205	52834.904
E		10	100	97374	41549.85
E		5	100	96105	43137.801

note: Group with the same letter are not significantly different

to the above, we summed all animal losses for each run. A total of 100 observations were obtained, and Table 9 provides the mean and standard deviation and test results. Overall, the best strategies are 11,15, 2,13, 6, 9, 1, 10, and 5, with the least animal losses (95,987; 71,129; 58,753; 56,454; 54,916; 40,665; 39,169; 37,263; and 36,458, respectively).

3.2.2.3 Scenario 3

In scenario 3, we assume that an FMD virus is introduced in large beef. Similarly, we summed all animal losses for each run. A total of 100 observations were obtained, and Table 10 provides the mean and standard deviation and test results. Overall, the best strategies are 11, 15, 2, 13, 6, 9, 1, 10, and 5, with the least animal losses (95,987; 71,129; 58,753; 56,454; 54,916; 40,665; 39,169; 37,263; and 36,458, respectively).

Table 9: Multiple Comparison for Animal Loss under Scenario 2

Group		strategy	observations	Mean	Standard Deviation
	A	3	100	451463	311225.154
	A	7	100	413217	287281.042
B	A	14	100	396657	258376.865
B	C	12	100	318849	230757.705
D	C	4	100	276745	289937.633
D		8	100	225086	262870.659
	E	11	100	95987	65544.36
	E	15	100	71129	60432.163
	E	2	100	58753	51104.354
	E	13	100	56454	47791.215
	E	6	100	54916	49765.921
	E	9	100	40665	50880.178
	E	1	100	39169	37318.808
	E	10	100	37263	33688.635
	E	5	100	36458	31974.882

note: Group with the same letter are not significantly different

Table 10: Multiple Comparison for Animal Loss under Scenario 3

Group		strategy	observations	Mean	Standard Deviation
	A	7	100	308553	315149.249
	A	14	100	302730	332409.258
	A	3	100	300179	320838.347
	B	12	100	140986	236813.119
	B	8	100	129991	229858.856
C	B	4	100	86696	149354.192
C		11	100	68167	77997.098
C		6	100	42263	63751.681
C		15	100	40342	58704.475
C		13	100	38559	55124.221
C		2	100	37080	54589.334
C		10	100	26733	51507.085
C		5	100	26589	51406.694
C		1	100	25826	50975.511
C		9	100	22428	57356.944

note: Group with the same letter are not significantly different

Table 11: Multiple Comparison for Animal Loss under Scenario 4

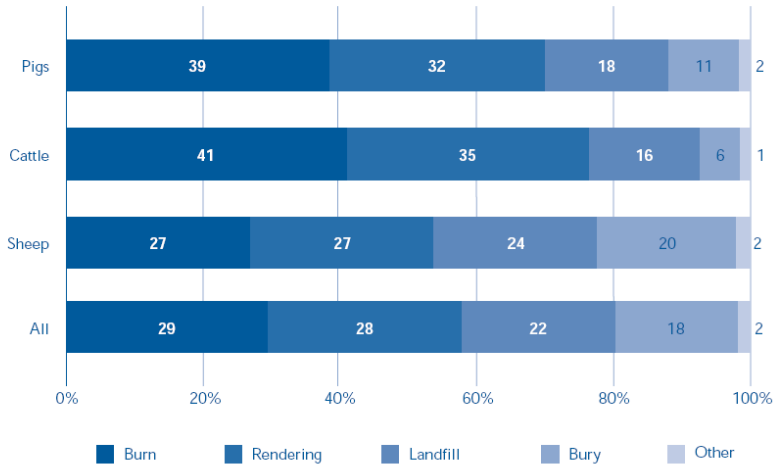
Group	strategy	observations	Mean	Standard Deviation
A	7	100	395905	282432.105
A	14	100	393286	305831.542
A	3	100	388452	290022.594
B	12	100	225179	173062.807
B	4	100	191224	307853.446
B	8	100	160615	261511.797
C	11	100	57380	86449.064
C	2	100	27558	47589.386
C	13	100	21671	35253.466
C	6	100	21344	43633.679
C	15	100	15044	30688.515
C	1	100	6633	16134.465
C	10	100	6094	15413.911
C	5	100	5607	14649.484
C	9	100	4463	20168.639

note: Group with the same letter are not significantly different

3.2.2.4 Scenario 4

Similarly, in scenario 4, we assume that an FMD virus is introduced in backyard. According to Table 11, the best strategies are 11, 2, 13, 6, 15, 1, 10, 5, and 9, with the least animal loss.

Overall, according to Tables 8- 11, the best mitigation strategies for all four scenarios are strategies 1, 5, 9, 10, and 15, with common strategy regular surveillance, slaughter of the infected animals, and early detection. In the following sections, we will use one of the best strategies, strategy 15, with ”worst” or largest animal loss to estimate the costs of disposing of animal carcasses and transportation under four different scenarios and to examine the effectiveness of the disposal strategies.



NOTES

1. The figures excludes animals slaughtered under the Livestock Welfare (Disposal) Scheme and in the three kilometre cull.
2. Burn includes incineration, on-farm burning and mass pyres.
3. Landfill includes mass burials.
4. Because of rounding numbers may not add up to 100.

Source: National Audit Office analysis of the Department's data.

Figure 14: Main Disposal Methods Used during the 2001 Outbreak

3.3 Carcass Disposal Options

During the 2001 U.K. FMD outbreak, the most commonly used methods during the whole epidemic were burning (29%) ,rendering (28%), landfill (22%), burial (18%) and (Other (2%) (Fig. 14), while during the 1997 Taiwan FMD outbreak, 5% of the carcasses were disposed of with open burning or incineration, 15% with rendering , and 80% by burial and public landfill (Ellis, 2006). Thus, there are several options in the study area, including incineration, composting, rendering, and burial.

3.3.1 Incineration

Incineration has historically played an important role in carcass disposal. During the 2001 U.K. FMD outbreak, about 29% of the carcasses were disposed of by incineration. Advances in science and technology, increased awareness of public health, growing con-

cerns about the environment, and evolving economic circumstances have all affected the application of incineration to carcass disposal. There are three broad categories of incineration techniques: open-air burning, fixed-facility incineration, and air-curtain incineration. Incineration is a viable way of disposing of animal carcasses. When incineration is complete, all disease-causing organisms are destroyed. The byproduct of the incineration process is ash, which can be land applied or buried.Direct variable cost associated with incineration is about $55.40 per mortality.

There are no general cost estimates of indirect costs associated with incineration. However, we need to consider (Mukhtar et al., 2008): environmental impacts, including the release of noxious gases and compounds, including dioxins; smoke and odor emission; disturbances due to operation of heavy machinery and trucks; soil disturbances, which typically increase the potential for erosion, and soil erosion from thermal sites, which may carry contaminants resulting in severe off-site impacts; impacts on water quality due to runoff from stored animals or process residues that might carry sediments and materials washed off equipment, and negative impacts on wildlife; additional costs of disease management from spread during transport and storage of animal carcasses; potential lost tourism if the thermal destruction becomes widely publicized; and movement restrictions on people and vehicles. There may also be indirect costs resulting from public opposition to the use of mass thermal sites, including legal fees (e.g., a best practices and guidelines for contaminated plant and animal disposal citation).

3.3.2 Rendering

Rendering is acceptable for disposing of livestock mortalities in Texas. It is the most effective means of minimizing human exposure to biological and chemical hazards when disposing of mortalities; proper rendering at temperatures that reach 295 ^{0}F kills all

pathogens (U.S. Food and Drug Administration (FDA), 2003). Moreover, rendering recycles the animal carcasses into useful byproducts (such as fatty acids, bone meal, and soap) by grinding the carcasses, cooking the grounds, and separating the liquid tallow (fat) from the solid material. Six rendering plants exist in the study area of Texas with relatively small capacity, increasing the likelihood that the mortalities will be out of range of the rendering facilities. Direct variable cost associated with rendering is about $60.68 per mortality.

3.3.3 Composting

Composting is an approved and potentially inexpensive way of disposing of livestock mortalities. If done correctly, composting can destroy many disease-causing organisms on site, eliminating potential for disease transmission off site. However, composting on a large scale increases the potential for disease transfer from one site to another, because wild or feral animals may dig into the compost and become a vector that can spread the disease. The byproduct of composting is a nutrient-rich material applicable to crop-producing areas.Direct variable cost association with composting is about $58.8 per mortality.

There are no general cost estimates of indirect costs associated with composting. However, we need to consider (Mukhtar et al., 2008) environmental impacts, including odor emissions; disturbances due to operation of heavy machinery and trucks; soil disturbances that typically increase the potential for erosion, and soil erosion from composting sites that may carry contaminants resulting in severe off-site impacts; impacts on water quality due to runoff from stored animals or process residues that might carry sediments and materials washed off equipment; negative impacts on wildlife; additional costs of disease management from spread during transport and storage of animal carcasses; potential lost tourism if the composting becomes widely publicized; movement restrictions on people and vehicles; the negative impacts on the landscape and subsequent intended use of the composting site

due to the potential change in allowed land use or vegetation; indirect cost resulting from public opposition to the use of mass composting sites, including legal fees; and additional costs to keep birds, flies and other insects, vermin, and scavenging animals (as the most important carriers of disease micro-organisms) away from the compost piles (best practices and guidelines for contaminated plant and animal disposal citation may result).

3.3.4 Burial

Burial is a common practice and is often the disposal method of choice for catastrophic livestock losses. Burying the animals on site as soon as possible after death dramatically lowers the possibility of a disease spreading to other areas of the state. Advantages of the burial method include cost effectiveness and security. Disadvantages of the burial method include difficulty in winter and the potential contamination of groundwater or surface waters with chemical products of carcass decay. Direct variable cost associated with burial is about $40 per ton (again, best practices and guidelines for contaminated plant and animal disposal citation may result). However, because of the high environmental cost, finally we assume the total cost (disposal cost plus environmental cost) is $100 per ton.

There are no general cost estimates of indirect costs associated with burial destruction. However, we need to consider (Mukhtar et al., 2008) the adverse environmental impacts, including air pollution due to odor emissions from burial sites; ground and surface water pollution resulting from leaching of waste emissions from buried animal carcasses or plants into underground water, or nearby surface stream pollution from disinfection, carcass fluids, and slurry, etc.; contamination of soils; negative impacts on wildlife and fisheries; potential lost tourism if the burial becomes widely publicized (a major factor in the U.K. carcass burning), and movement restrictions on people and vehicles; the negative impacts on the landscape and subsequent intended use of the burial site due to the potential change

in allowed land use or vegetation (best practices and guidelines for contaminated plant and animal disposal citation could result); indirect cost resulting from public opposition to the use of mass burial sites, including legal fees, additional security cost along the transportation routes and surrounding areas if animal carcasses have to be disposed of off-site, and potential security costs on site to keep animals from digging up buried carcasses. The latter can be minimized if proper overlay is provided. Burial on private land can also impact future land use and land values, especially if legislation requires that carcass burial be listed on the property deed (again, a best practices and guidelines for contaminated plant and animal disposal citation may result).

In general, the rank of environmentally preferred disposal methods from the most to the least is rendering, incineration, composting, and burial.

3.4 Method for Analyzing Animal Carcass Disposal Costs

The goal of the optimal disposal model is to minimize total disposal costs including disposal and transportation costs. These costs are subject to many constraints, including types of different disposal facilities (fixed vs. mobile), the capacity of each facility, and the availability of various disposal methods. Based on the simulated disease outbreaks, the ”best” disposal technique(s) during the course of disease outbreak that minimize the potential total disposal cost will be determined based on the contemporary and spatial distribution of daily carcass disposal load and the available capacities of disposal facilities in the event area.

3.4.1 Model Assumption

i. Capacity Assumption

Because the capacity of the disposal location is unavailable, we assumed that each lo-

cation has the capacity to process about 200 tons per day, or 400 mortalities per day.

ii. Mobile Facility Application

A mobile facility is only feasible for the incineration method. With environmental concern and its disposal scale, we assume that this method is only used on the infected premises with less than 10 cattle.

iii. Transportation Cost

Unit transportation cost is estimated as $1.00 per mile and 5 tons per truck per trip (Catastrophic Animal Mortality Management Plan), and an out-of-study-area fixed disposal plant is not considered an option.

iv. Burial Assumption

Although burial involves time effectiveness, it has the deepest impact on the environment. The burial method will be applied only when other methods are unavailable or their capacities are exhausted, and disposal cost plus environmental cost is assumed as $100 per ton.

v. Disposal Time Assumption

According to risk of infection and the number of cattle, the estimated disposal time is shown in Table 12.

3.4.2 Mixed-Integer Programming Model

We divided the total carcass disposal cost into two components: costs of disposal facilities and transportation costs of moving animal carcasses.

The minimization of animal carcass disposal costs faces constraints. Specifically, we impose the following constraints:

Table 12: Disposal Time by Herd Type

FARM	TYPE	Description	Disposal time
1	feedlot1	Company owned feedlot (>50,000 head)	28
2	feedlot2	Stockholder feedlot (>20,000 but < 50,000)	28
3	feedlot3	Custom feedlot (>5,000 but < 20,000)	21
4	feedlot4	Backgrounder feedlot	14
5	feedlot5	Yearling-pasture feedlot	14
6	feedlot6	Dairy Calf-raiser feedlot	14
7	small beef	<100 cattle	5
8	large beef	> 100 cattle	10
9	small dairy	<1000 number dairy cows	7
10	large dairy	>1000 number dairy cows	5
11	backyard	<10 cattle	1
12	small ruminant	sheep and goats	3
13	swine pig	concentrated animal feeding operations	10

(a) Carcass load balance constraints: The total carcasses transported from location s cannot exceed the carcass load at location s.

(b) Disposal capacity constraints: The total carcasses transported to disposal location k cannot exceed disposal capacity of location k.

Therefore, the cost minimization for animal carcass disposal can be written as

$$\sum_t \sum_f \sum_k DC_{fk} CD_{fkt} + \sum_t \sum_s \sum_k TC_{sk} T_{skt} \tag{3.1}$$

Subject to

$$\begin{cases} \sum_k T_{skt} \leq LOAD_{st} \\ -\sum_s T_{skt} + \sum_f CD_{fkt} \leq 0 \end{cases} \tag{3.2}$$

where f denotes the type of fixed disposal facility, k is the locations of disposal facilities, s is the locations of carcasses, and t is time. The choice variables for the cost minimization of animal carcass disposal consist of T_{skt} and CD_{fkt}, with T_{skt} being the number of carcasses

transported from site s to disposal site k during time t, and CD_{fkt} being the number of carcasses disposed of at disposal site k via method f during t.

3.5 Application

Data used in this chapter are from the Ausspread model described in Chapter II. We selected four different scenarios-FMD disease introduced from large feedlots, small feedlots, large beef, and backyard. For each scenario, we selected the largest events simulated from the Ausspread model.

3.5.1 Selection of Burial Locations

Figures 15- 18 are the distribution maps of carcass load and fixed disposal locations under the scenario that an FMD disease is introduced into large feedlots, small feedlots, large beef, and backyard, respectively.

Figure 15 is the carcass load under a scenario that an FMD disease is introduced into large feedlots. In the figure, the red stars represent the fixed disposal locations of incineration methods, the triangle is the composting method, the circle is rendering, and the cylinders represent the number of cattle. Figure 15 shows that there are large numbers of cattle (over 60,000) needing to be disposed of in regions 1,3,4, and 5, which means the disposed carcasses per day are over 2,000, indicating that the burial method is needed. Similarly, there are large numbers of carcasses needing to be disposed of in region 1 of Fig. 16, region 2 of Fig. 17, and region 2 of Fig. 18. Those results from approximately 70% of feedlots with over 10,000 cattle located in Deaf Smith, Parmer, and Castro Counties (Fig. 19). Figure 19 not only shows the distribution of large feedlots but also shows the distributions of roads and hydrology. The three ”best” mass burial locations are red circles with low population density(Since population density is unavailable, we use road density

to represent it.) and far from hydrologic circles. We treat the mass-burial method as fixed disposal facilities, and the carcass transportation distance will be calculated as the distance between the center of the burial locations and the carcass load locations.

3.5.2 Scenario 1

In scenario 1, we assume that an FMD virus is introduced in large feedlots. The largest animal loss in the Ausspread model among 100 random runs is approximately 337,000. By the mixed-integer program model, the total cost is estimated at about $33.3 million, including disposal cost of $28.4 and transportation cost of $5 million (Table 13). Average total cost under scenario 1 is about $98.9 per mortality, including disposal cost of $84.10 and transportation cost of $14.80 per mortality, implying that the average transportation distance is approximately 29.6 miles.

Table 13: Estimated Costs under Different Scenarios

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Total(M)	Unit	Total(M)	Unit	Total(M)	Unit	Total(M)	Unit
Disp.	28.4	84.1	28.6	84.3	26.7	83.4	12.8	68.2
Trans.	5	14.8	7.2	21.2	7.5	23.4	3.6	19.4
Total	33.3	98.9	35.8	105.5	34.2	106.8	16.4	87.6
Animal loss	337,149		339,529		320,278		187,312	

Note: Disp. is the disposal cost.
Trans. is the transportation cost.

3.5.3 Scenario 2

In scenario 2, we assume that an FMD virus is introduced in small feedlots. The largest animal loss is approximately 339,000. The total cost is estimated at about $35.8 million, including disposal cost of $28.6 million and transportation cost of $7.2 million

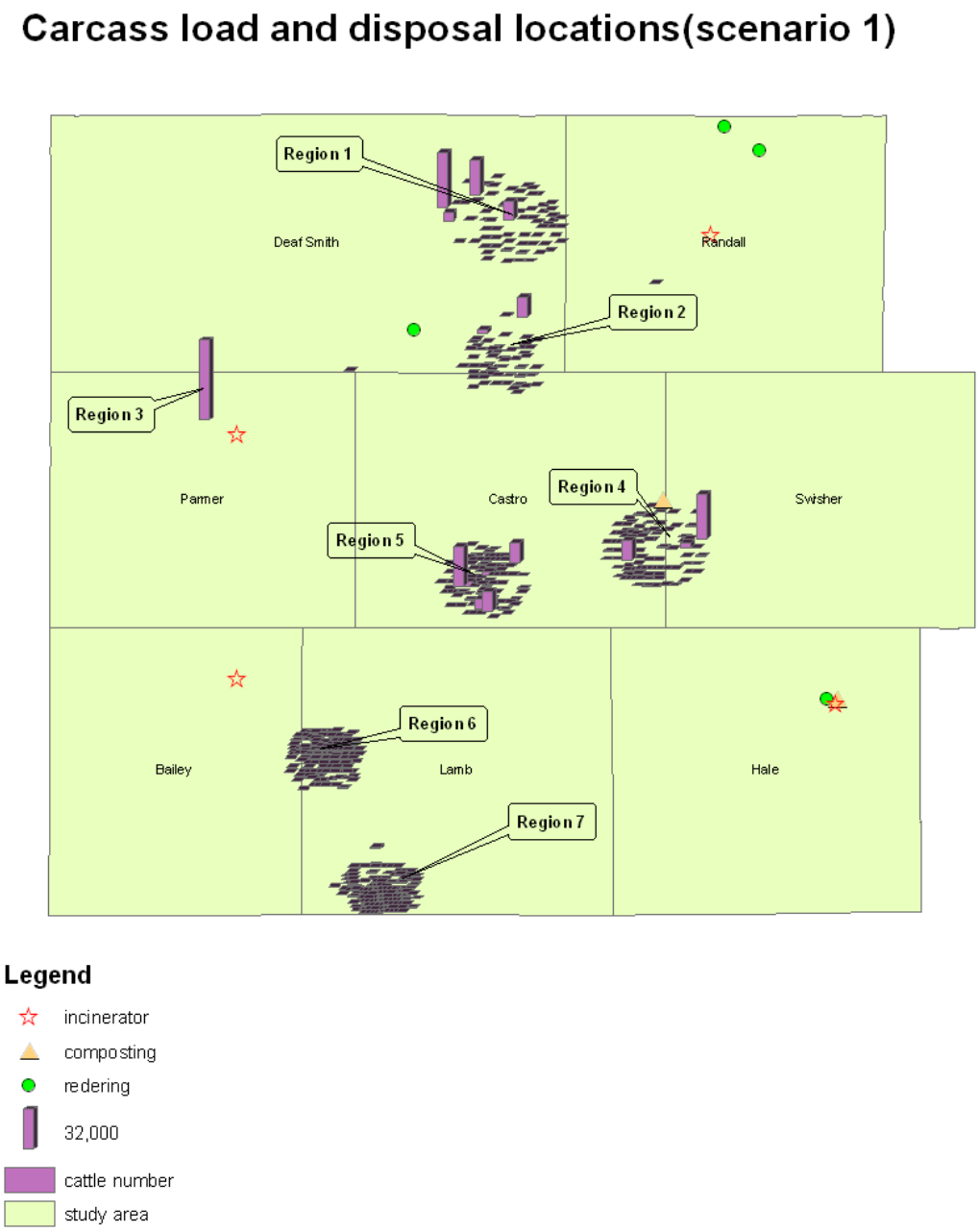


Figure 15: Carcass Load and Fixed Disposal Locations under Scenario 1

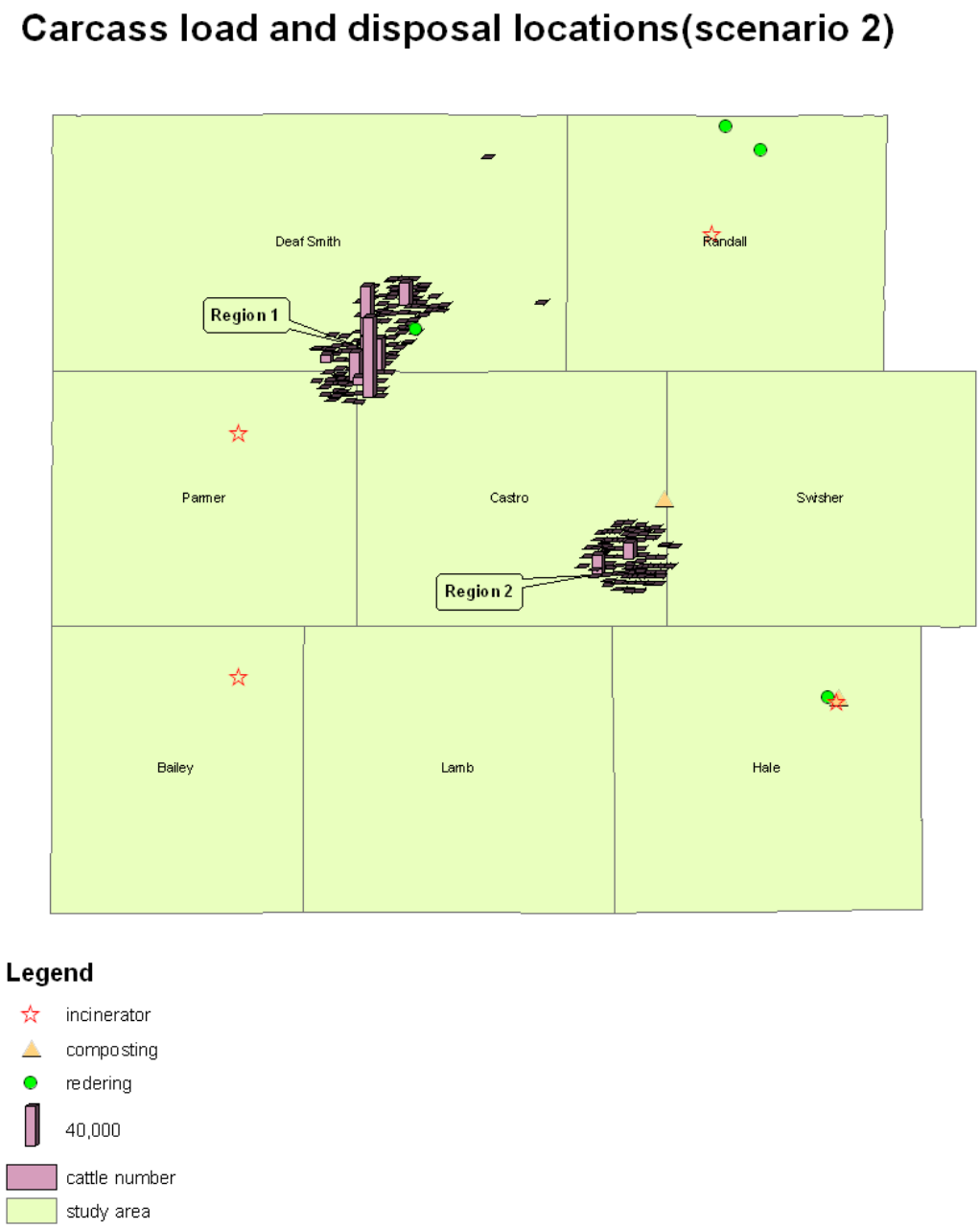


Figure 16: Carcass Load and Fixed Disposal Locations under Scenario 2

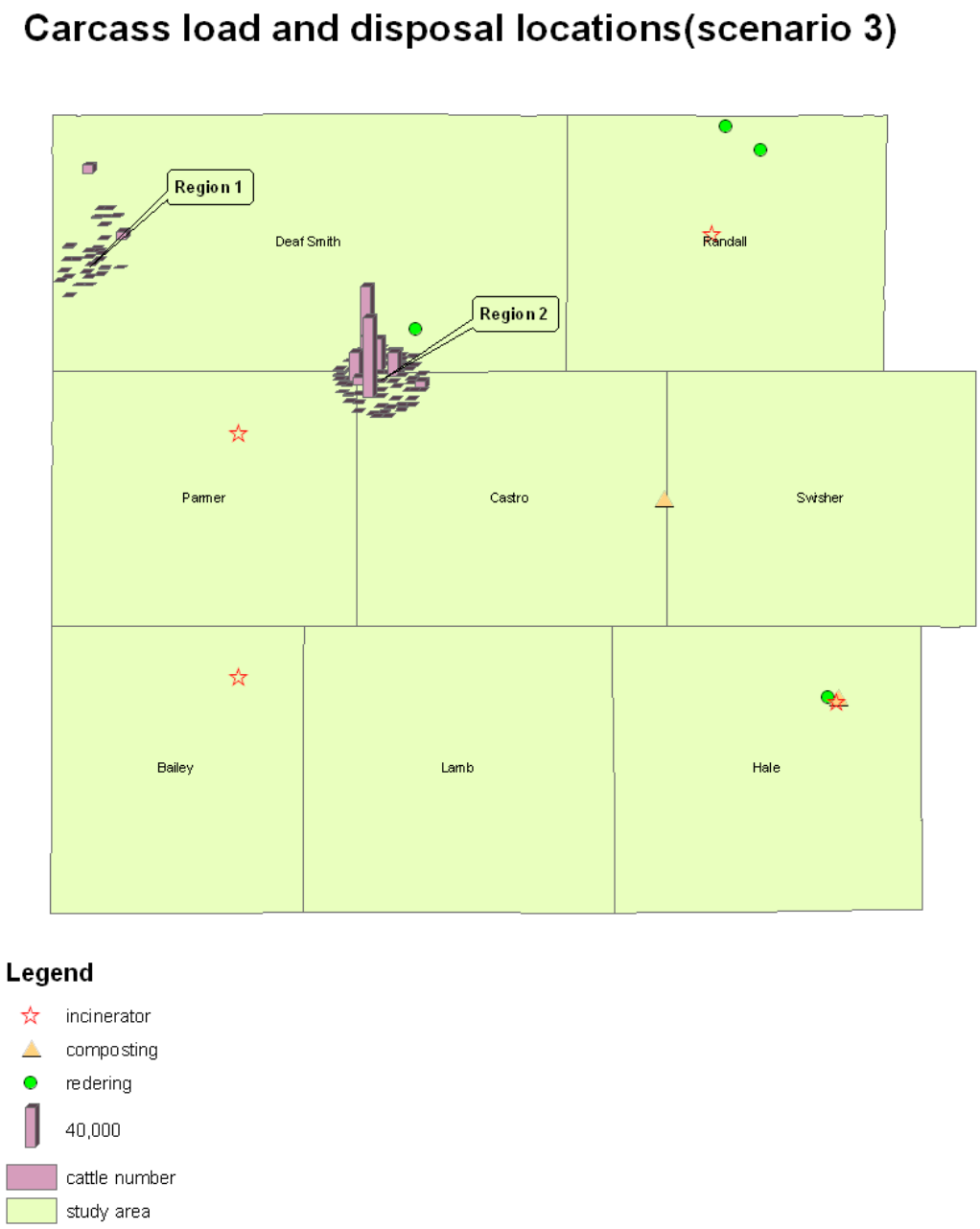


Figure 17: Carcass Load and Fixed Disposal Locations under Scenario 3

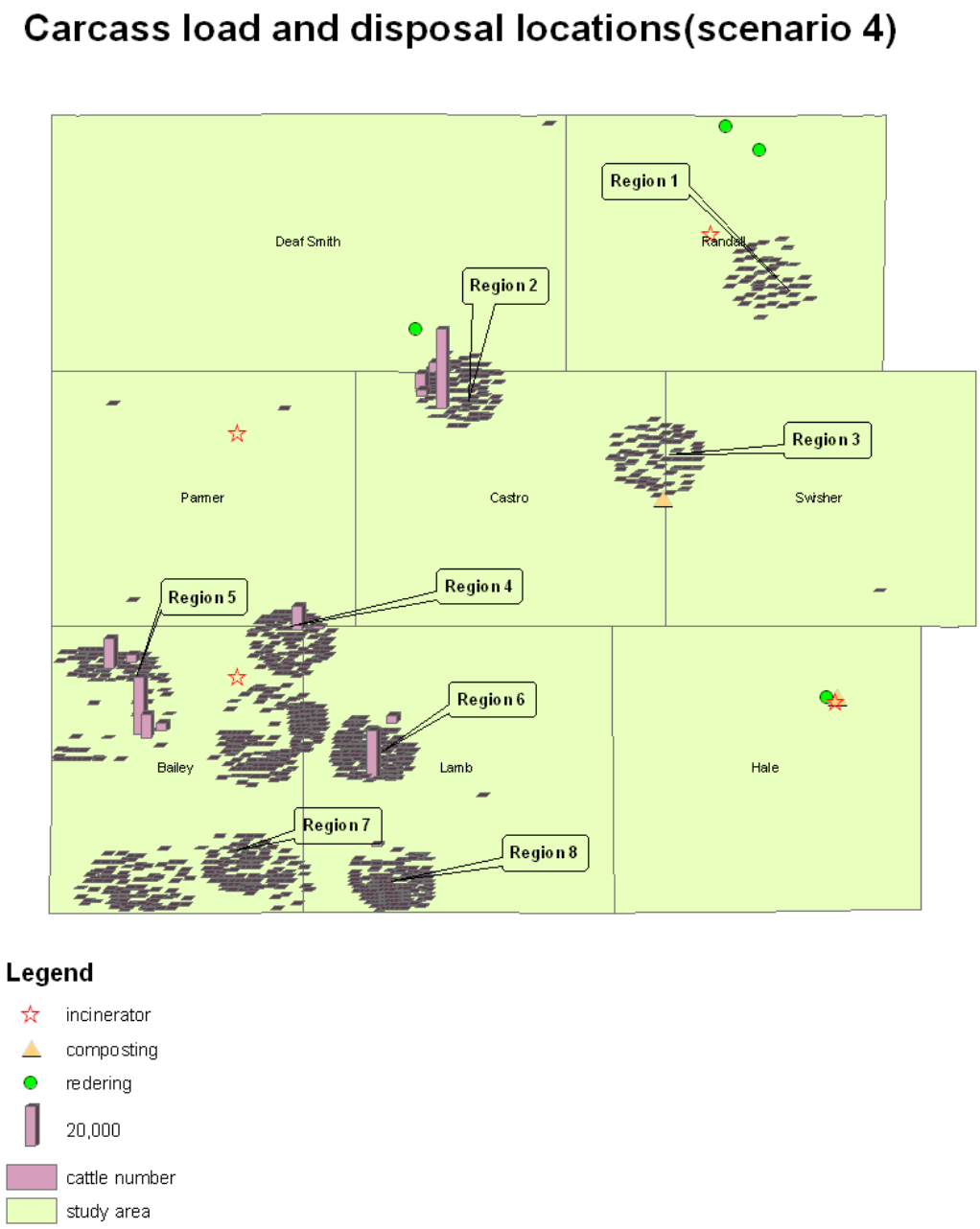


Figure 18: Carcass Load and Fixed Disposal Locations under Scenario 4

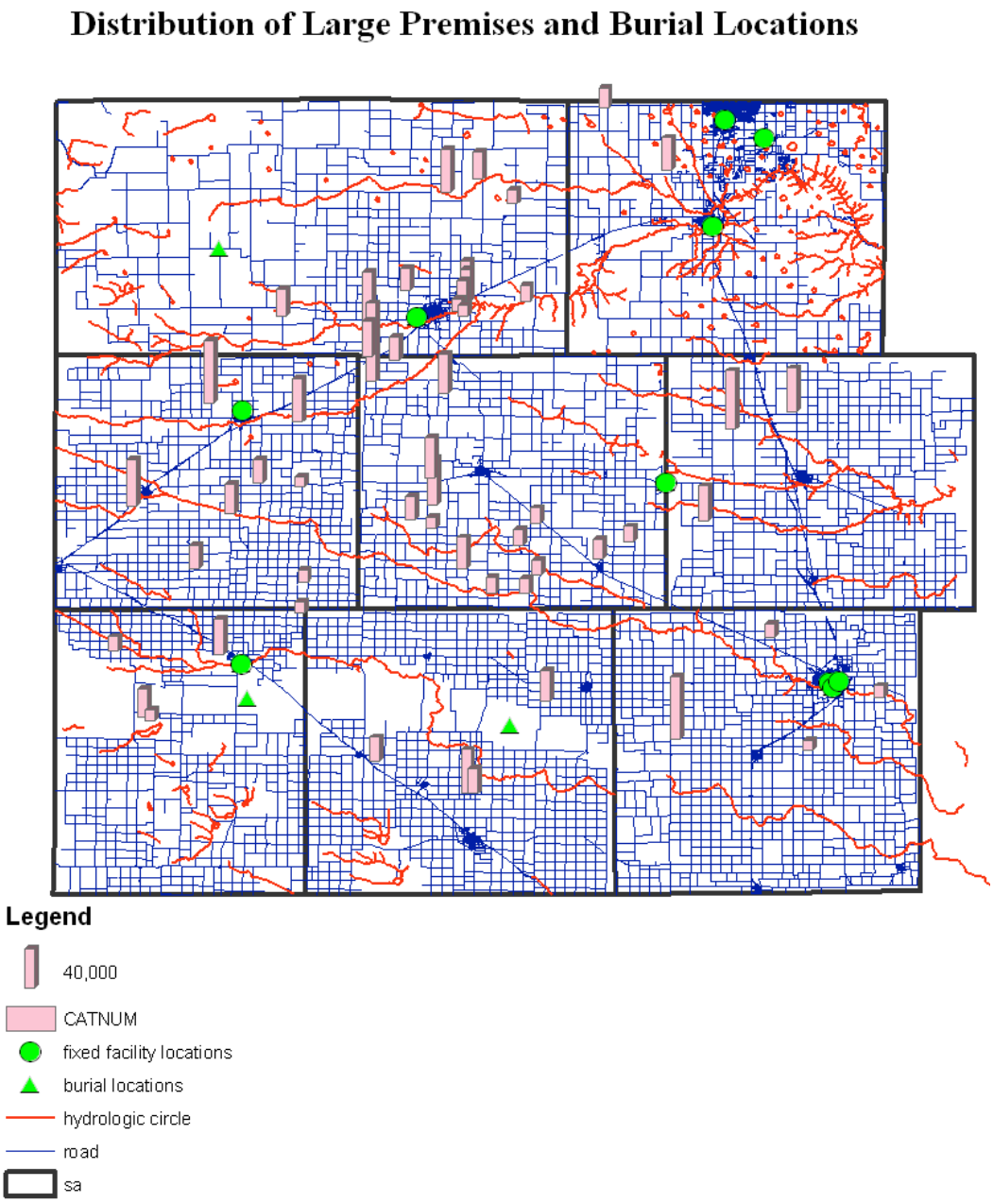


Figure 19: Large Premises Distribution and Burial Locations

(Table 13). Average total cost under scenario 2 is about $105.50 per mortality, including disposal cost of $84.30 and transportation cost of $21.20 per mortality, implying an average transportation distance of approximately 42.4 miles.

3.5.4 Scenario 3

In scenario 3, we assume that an FMD virus is introduced in large beef. The largest animal loss is approximately 320,000. The total cost is estimated at about $33.3 million, including disposal cost of $28.4 million and transportation cost $5.0 million (Table 13). Average total cost under scenario 3 is about $98.90 per mortality, including disposal cost of $83.40 and transportation cost of $23.40 per mortality, implying an average transportation distance of approximately 46.8 miles.

3.5.5 Scenario 4

In scenario 4, we assume that an FMD virus is introduced in large feedlots. The largest animal loss is approximately 187,000. By the mixed-integer program model, the total cost is about $16.4 million, including disposal cost of $12.8 million and transportation cost of $3.6 million (Table 13). Average total cost under scenario 4 is about $98.90 per mortality, including disposal cost of $68.20 and transportation cost of $19.40 per mortality, implying an average transportation distance of approximately 38.8 miles.

3.6 Discussion

In this chapter, we first tested the best mitigation strategies with average minimum animal loss by the Tukey test, and the results showed the best mitigation strategies for all four scenarios are strategies 1, 5, 9, 10, and 15. Then we used one of the best strategies, strategy 15, with the ”worst” or largest animal loss to estimate costs of disposing of animal car-

casses and transportation under four different scenarios, and we examined the effectiveness of the disposal strategies.

From the results in Table 13, the estimated average highest disposal cost is under scenario 2, while the lowest is under scenario 4, because it had the largest-scale carcass disposal. When the lower-cost disposal method is exhausted, higher-cost disposal methods will be needed. Thus, the unit disposal cost will vary with carcass scale. The unit transportation cost also varies by the distributions of the infected premises and disposal locations. The estimated unit transportation cost is lower under scenarios 1 and 4 and higher under scenarios 2 and 3 because under scenarios 2 and 3 the infected premises are more highly concentrated, which causes less optimal options on transportation for the infected premises.

Approximately 70% of feedlots with over 10,000 cattle are located in Deaf Smith, Parmer, and Castro Counties. It is necessary to per-select burial locations or build new fixed disposal locations to reduce transportation costs. In Fig. 9, we selected three burial locations for mass carcass disposal, but this is relatively rough, and further selection of burial locations can be done if more detailed GIS data are available.

CHAPTER IV

ANALYSIS OF THE IMPACT OF FMD ON THE STOCK MARKET IN THE U.K.

4.1 Introduction

Foot-and-mouth disease can have a devastating impact on food production and the economy of rural areas in the infected country (Rich and Winter-Nelson, 2007). It can spread rapidly, threaten animal welfare and health, and distort international trade. An FMD outbreak typically removes animals from the market, closes export markets, and can reduce domestic demand for animal products. If trade restrictions take place, producers in export-oriented countries can be affected especially badly. There can also be considerable uncertainty and variation in outcomes.

During the 2001 U.K. outbreak, FMD was suspected at an abattoir in Essex on February 21 and confirmed the following day. On February 21, the European Union's Standing Veterinary Committee banned related United Kingdom exports. In mid-March, at the height of the crisis, there were more than 40 confirmed cases per day. The epidemic lasted for 32 weeks, with the last case being confirmed on September 30, 2001. The Treasury of the U.K. has estimated that the net economic effect of the outbreak was about 0.2% of gross domestic product.

Index investing, including whole market or industry index investing, has gained tremendous popularity in the past decade or so. There are many advantages of including an index fund in one's portfolio rather than holding only individual stocks. These advantages include a reduction in trading costs and management fees, diversification of risk, postponement of

taxable gains, and obtaining market predictability. Over an FMD period, investors are exposed in a more risky environment and become more vulnerable, and thus it is essential to understand how the market and industry indexes as well as individual firm stock prices behave over time, especially following events such as an FMD outbreak. Investors and policymakers should be concerned with whether or not a major event may lead to a sudden change in return volatility and how unanticipated shocks will affect volatility over time.

FMD seems to have varying impacts on equity markets. To investigate the differences, we studied returns at three different levels of the stock market: the whole-market level, the individual-industry level, and the individual-firm level. Each level includes two different markets, as follows.

1. The whole-market level is represented by FTSE 100 and FTSE 250
    - The FTSE 100 is a major stock market in the U.K. The first 100 highly capitalized companies listed on the London Stock Exchange are listed on the FTSE 100 index, and FTSE 100 companies represent about 81% of the market capitalization of the whole London Stock Exchange. As of September 30, 2008, the net market capitalization of the FTSE 100 Index was £1,171 billion. Thus, it was selected to represent a highly capitalized market.

    - The FTSE 250 is a capitalization-weighted index of 250 U.K. companies on the London Stock Exchange. They are selected quarterly as being the 101st to 350th largest companies with their primary listing on the exchange. As of September 30, 2008, the net market capitalization of the FTSE 250 Index was £161 billion (or 13.7% of the FTSE 100 Index). It was selected to represent relatively small capitalized market.
2. The food product and retail industry is represented by the food product index and the

food and drug retail index.

- The food product index firms were selected from the FTSE 350, which is a combination of the FTSE 100 Index of the largest 100 companies and the FTSE 250 Index of the next largest 250. It represents the entire food product industry.
- The food & drug retail index firms were selected from the FTSE 350 and represent the entire food product and food and drug retail industries.

3. The individual food product firm level is represented by Associated British Foods (ABF) and Devro.
   - Associated British Foods operates in most of the world's main food markets. Its business includes: grocery, sugar and agriculture, ingredients, and retail. Thus, we selected it to represent non-meat-product firms.
   - Devro, a public limited firm registered in Scotland, is one of the world's leading producers of manufactured casings for the food industry, supplying a wide range of products and technical support to manufacturers of sausages, salami, hams, and other cooked meats. It was selected to represent meat-product firms.

Volatility is a widely used measure of market risk and is often referred to as the "investor fear gauge"-a large amount of volatility is a result of investor fear or uncertainty, while low values generally correspond to less stress. According to an asset-pricing model, the current price of an asset is related to the expected volatility persistence. This implies that correctly estimating volatility persistence in returns will help us build accurate asset pricing models and will yield superior forecasts for return volatility. Financial market participants are interested in knowing what events can alter the volatility pattern of financial assets and how unanticipated shocks determine the persistence of volatility over time. An event outbreak such as FMD could lead to more risk for investors. The purpose of this paper is to measure the impact of the announcement of confirmed cases of FMD disease

on market, industry, and firm-level volatility of return. It may help investors to understand risk and build accurate asset pricing models, which can yield superior forecasts of return volatility.

This chapter is organized as follows. Section II discusses methods used, including summary statistics, univariate GARCH (1,1), and modified GARCH (1,1) in a mean model. Section III contains the empirical results and robustness check by a rolling window model and the final section presents a summary.

4.2 Method

4.2.1 Summary Statistics

Let $P_{k,t}$ be the stock k price at time t. Thus, we have

$$R_{k,t} = ln\frac{P_{k,t-1}}{P_{k,t}} = \mu_k + \varepsilon_{k,t} \tag{4.1}$$

where P is the stock index or price; $R_{k,t}$ is the continuously compounded return of the kth stock index over the period t - 1 to t; μ_k is the estimated mean of the kth stock price;
k = 1,...,6 represents six different stock indexes, including FTSE 100, FTSE 250, food product, food and drug retail, Associated British Food, and Dervo; and
$\varepsilon_{k,t}$ is the error term of the kth stock price at time t.

The unconditional mean (μ_k) and unconditional variance (σ_k^2) of $R_{k,t}$ can be naturally defined as

$$\mu_k = E(R_{k,t})$$

$$\sigma_k^2 = E[(R_{k,t} - \mu)^2].$$

Further, the daily volatility (DV) and annual volatility (AV) were defined as

$$DV_k = sd(R_{k,t}) = \sigma_k$$

$$AV_k = DV_k \times \sqrt{252} = \sigma_k \times \sqrt{252}$$

Those first and second moments of continuously compounded returns will be used to measure and compare both the return and risk of each series. Furthermore, a Wilcoxon-Mann-Whitney test, a nonparametric test for mean difference, and an F-test will be employed to test mean and variance difference between the FMD and non-FMD periods.

Higher moments of the return often figure prominently in volatility models. The unconditional skewness and kurtosis are the third and fourth moment of the continuously compounded return, defined as

$$Skewness = \frac{E[(R_{k,t}-\mu)^3]}{\sigma^3}$$

$$Kurtosis = \frac{E[(R_{k,t}-\mu)^4]}{\sigma^4}$$

Those will be used to measure and compare both the excess return and the risk of each series between the FMD and non-FMD periods.

4.2.2 GARCH Analysis and Detecting Structure Break

The auto-regressive conditional heteroskedasticity (ARCH) model (Engle, 1982) provides a means of describing the evolution of a conditional heteroskedasticity process as a distributed lag of past squared residuals. It is a widely used class of models for the conditional volatility and has been extended by Bollerslev (1986). Based on the work of

Engle and Bollerslev (1986) and Bollerslev (1986), (Nelson, 1990) establishes necessary and sufficient conditions for the stationarity and ergodicity of the GARCH (1,1) process.

A member of the ARCH class of models is the GARCH (p, q) model, with its process characterized by the first two conditional moments:

$$\begin{aligned} R_t &= \mu + \varepsilon_t \\ \varepsilon_t &= \eta_t \sqrt{h_t} \\ h_t &= \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \end{aligned} \tag{4.2}$$

where $\omega > 0$, $\alpha_i > 0$, $\beta_i > 0$ for all i, and η_t is a sequence of i.i.d. random variables with zero mean and variance 1.

A popular member of GARCH (p,q) is GARCH (1,1) (equation 4.3), which is the most robust of the family of volatility models. Also, the GARCH (1,1), Eq. 4.3, can be rewritten in terms of the unconditional variance as Eq. 4.4:

$$\begin{aligned} R_t &= \mu + \varepsilon_t \\ \varepsilon_t &= \eta_t \sqrt{h_t} \\ h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \end{aligned} \tag{4.3}$$

$$\begin{aligned} R_t &= \mu + \varepsilon_t \\ \varepsilon_t &= \eta_t \sqrt{h_t} \\ h_t &= \sigma^2 + \alpha(\varepsilon_{t-1}^2 - \sigma^2) + \beta(h_{t-1} - \sigma^2) \end{aligned} \tag{4.4}$$

where $\sigma^2 = \omega(1 - \alpha - \beta)^{-1}$ is the unconditional variance. When $\alpha + \beta < 1$, the

conditional variance reverts to its mean value σ^2 at a geometric rate of $\alpha+\beta$. This structure allows mean reversion at a reasonable rate only if $\alpha + \beta$ is very close to unity. The sum of α and β in Eq. 4.3 also measures the persistence of volatility for a given shock, and a value of one would entail an integrated GARCH (IGARCH) process, implying that shocks have a permanent effect on the variance of a series.

The GARCH (1,1) model also can be used to compute 95% conditional predicted intervals by the equation

$$95\%\text{CI}=\mu \pm 1.96 \times \sqrt{h_t}$$

where μ is the predicted return over the FMD period because according to the mean equation $R_t = \mu + \varepsilon_t$ the best predicted estimator for return is μ. The square root of conditional variance(h_t) is conditional volatility or standard deviation.

A commonly used time series analysis to test for the presence of a structural break is the Chow test.

$$\frac{(S_c-(S_1+S_2))/k}{(S_1+S_2)/(N_1+N_2-2k)} \sim F_{k,N_1+N_2-2k}$$

where S_c is the sum of squared residuals from the combined data, S_1 is the sum of squares from the first group, and S_2 is the sum of squares from the second group. N_1 and N_2 are the number of observations in each group, and k is the total number of parameters. The test statistic is compared with an F-distribution having k and $N_1 + N_2 - 2k$ degrees of freedom.

4.2.3 Modified GARCH-in-Mean model

The volatility characteristics outlined are univariate, relating the volatility of the series to only information contained in that series history. However, it is impossible that financial asset prices evolve independently of the market around them (Engle and Andrew, 2001).

The standard GARCH (p,q)-M process suggested by Bollerslev (1986) for stock excess return, R_t, is given by

$$\begin{aligned} R_t &= \delta\sqrt{h_t} + \varepsilon_t \\ h_t &= \omega + \sum_i^p \alpha_i \varepsilon_{t-i}^2 + \sum_i^q \beta_i h_{t-i} \end{aligned} \tag{4.5}$$

where $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}\varepsilon_t^2 = h_{t-1}$. The univariate GARCH-M model specifies the conditional mean and variance function and assumes that the information set consists only of the past innovations to the excess return, Rt. Hence, the only new information that becomes available at date t - 1 is . If future variance is not a function only of the squared innovation to current return, then a simple GARCH-M model is misspecified and any empirical results based on it alone are not reliable (Glosten, Jagannathan, and Runkle, 1993).

Engle, Lilien, and Robins (1987) suggested a modeling technique to analyze volatility in financial markets as follows:

$$
\begin{aligned}
R_t &= X_t^{'}\beta + \delta\sqrt{h_t} + \varepsilon_t \\
\varepsilon_t &= \sqrt{h_t}\eta_t \\
h_t &= \omega + \sum_{i}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i}^{q} \alpha_i h_{t-i}
\end{aligned}
\tag{4.6}
$$

where X is a vector of regressors, and the sign and size of parameter δ capture the direction and strength of the risk-return relationship. Parameter restrictions on the conditional volatility equation are the same as for the GARCH model.

Glosten et al. (1993) developed a modified GARCH (p,q)-M model to input seasonal indicator variables I_t into a conditional mean equation, and exogenous variables X_{t-1} into a conditional variance equation, as follows:

$$
\begin{aligned}
R_t &= \mu + \alpha I_t + \delta\sqrt{h_t} + \varepsilon_t \\
\varepsilon_t &= \sqrt{h_t}\eta_t \\
h_t &= \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \gamma X_{t-1}
\end{aligned}
\tag{4.7}
$$

This type of model could offer a structural or economic explanation for volatility.

In our case, we use the modified GARCH (1,1)-M to measure the different impacts of FMD on whole economics, food product and retail industrial, and individual food product firms. Model 1 can be written as

MODEL 1

$$R_{k,t} = \mu_k + \lambda FMDT_t + \delta\sqrt{h_{k,t}} + \varepsilon_{k,t}$$
$$\varepsilon_{k,t} = \sqrt{h_t}\eta_t \tag{4.8}$$
$$h_{k,t} = \omega_k + \alpha_k\varepsilon^2_{k,t-1} + \beta_k h_{k,t-1} + \gamma Dcase_{k,t}$$

where k = 1,...6 represent six different series, and FMDT is the indicator variables, which are 1 if during the FMD outbreak period and otherwise 0. Dcase is the first difference of scheduled announcement of the number of confirmed cases. The difference represents the shock of news or difference between investor expectation and the announcement if we assume that the investor's expectation is only based on the latest information. Intuitionally, the return is taken as the first difference, which means that taking the difference for the number of confirmed cases represents a co-movement with return.

Although our objective is to measure the impact of the number of confirmed cases on volatility, some other variables may be helpful in explaining or improving the model estimate. We could add indicator variables into the conditional variance equation, including the September 11 events (S11), which is 1 if the date is 9/11/2001, and otherwise 0, and the FMD period (FMDT), which is 1 if the date is between Feb. 20 and Sept. 30, 2001, and otherwise 0. Therefore, in model 2 through model 4, we add different combinations of these variables. These models are shown as

MODEL 2

$$R_{k,t} = \mu_k + \lambda FMDT_t + \delta\sqrt{h_{k,t}} + \varepsilon_{k,t}$$
$$\varepsilon_t = \sqrt{h_{k,t}}\eta_t \tag{4.9}$$
$$h_{k,t} = \omega_k + \alpha_k\varepsilon^2_{k,t-1} + \beta_k h_{k,t-1} + \gamma Dcase_{k,t} + \psi S11$$

In model 2, we add only S11 into the conditional variance equation.

MODEL 3

$$R_{k,t} = \mu_k + \lambda FMDT_t + \delta\sqrt{h_t} + \varepsilon_{k,t}$$
$$\varepsilon_t = \sqrt{h_t}\eta_t \tag{4.10}$$
$$h_{k,t} = \omega_k + \alpha_k\varepsilon^2_{k,t-1} + \beta h_{k,t-1} + \gamma Dcase_{k,t} + \phi FMDT_t$$

In model 3, we add only FMDT into the conditional variance equation.

MODEL 4

$$R_{k,t} = \mu_k + \lambda FMDT_t + \delta\sqrt{h_t} + \varepsilon_{k,t}$$
$$\varepsilon_t = \sqrt{h_t}\eta_t \tag{4.11}$$
$$h_{k,t} = \omega_k + \alpha_k\varepsilon^2_{k,t-1} + \beta_k h_{k,t-1} + \gamma Dcase_{k,t} + \psi S11 + \phi FMDT_t$$

In model 4, we add both S11 and FMDT into the conditional variance equation.

All models discussed in this section are estimated by maximizing the log-likelihood function for the model, assuming that $\varepsilon_{k,t}$ is conditionally normally distributed. However, Bollerslev and Wooldridge (1992) pointed out that even if this assumption is incorrect, as long as the conditional means and variances are correctly specified, the quasi-maximum likelihood estimates will be consistent and asymptotically normal. The MLE estimate is still appropriate if the conditional means and variances are correctly specified.

To determine the best-fitted specification, we use the likelihood ratio test, AICc , SIC, and HQIC criteria. They are

$$\text{AICc}=k\frac{2n}{(n-k-1)}\text{-2log(likelihood)},$$

$$\text{SIC}=\text{kln(n)-2log(likelihood)},$$

$$\text{HQIC}=\text{2klnln(n)-2log(likelihood)}$$

4.3 Application and Results

4.3.1 Summary Statistic

We use daily close price data on the six series listed above, over the period April 6, 1999 to December 29, 2005, representing 1,738 observations. Figure 20 plots the index or price for the six series. Over the FMD period, February 20 to September 30, 2001, the indexes of the FTSE 100 and FTSE 250 decreased from 4003.42 to 3276.11, or about 18.1%, and 4436.06 to 3490.79, or about 21.3%, respectively (Fig. 20). The food product and food and drug retail industries' indexes only decreased about 4.5% and 0.3%, respectively (Fig. 20). For individual food product companies, Associated British Foods and Dervo, their market prices decreased about 11.66% and 18.97%, respectively (Fig. 20).

We take the log-difference of the value of the series so as to convert the data into continuously compounded returns. The descriptive statistics for the return of those six series in Table 14 are the (1) the mean; (2) the Wilcoxon-Mann-Whitney test, a non-parametric test for mean difference; (3) the standard deviation; (4) the F-test for different variance; (5) skewness; and (6) excess kurtosis.

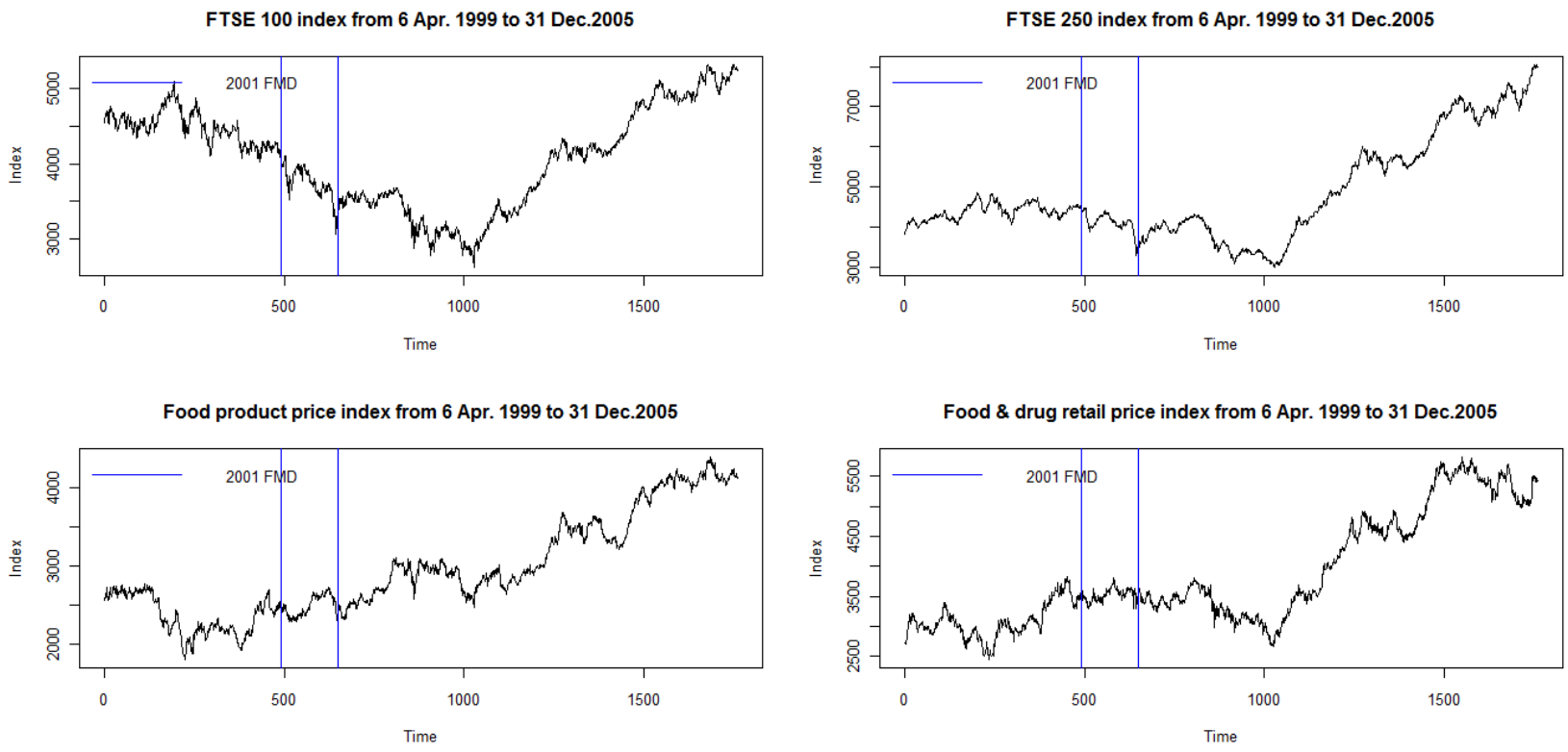
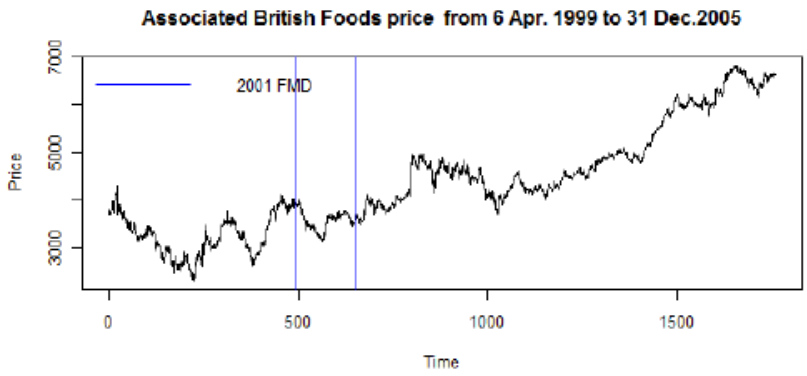


Figure 20: The Impact of the FMD on Stock Markets



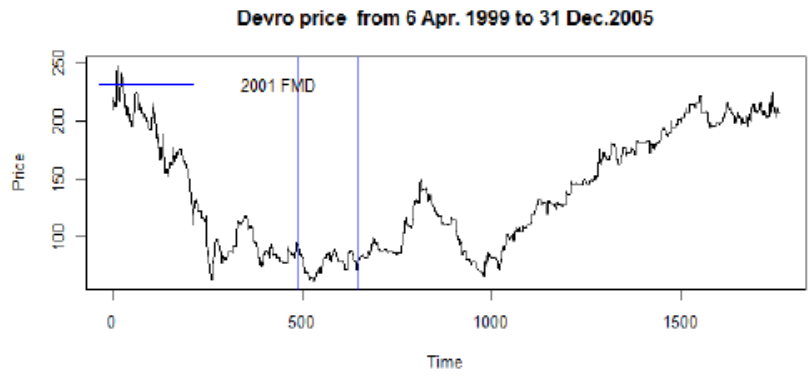


Figure 20: Continued

Table 14: Summary Statistics for Six Series

	Mean		Wilcoxon test		Standard error		F-TEST		Skewness		Kurtosis	
.	Non-FMD	FMD	Test Stat.	p-value	Non-FMD	FMD	F-Stat.	p-value	Non-FMD	FMD	Non-FMD	FMD
FTSE100	-.00003	-.004	-1.13	0.25	0.0115	.0150	1.685	$< .0001$	-.148	-.404	5.35	4.27
FTSE250	.0002	-.003	2.29	.02	0.0084	.0101	1.457	.0006	-.395	-.926	4.845	6.170
Food product	-.00028	-.0002	.817	.414	0.0124	.0127	1.037	.730	-.292	-.224	6.918	3.32
Food retail	-.00036	-.002	.47	.63	0.0140	.0142	1.03	.768	.109	.171	5.55	5.60
ABF	-.00049	-.0003	1.40	.16	0.0176	.0144	.663	.001	.383	.301	13.46	4.076
Devro	-.00094	-.005	.205	.837	0.0196	.0226	1.327	.010	1.258	-.108	17.67	13.24
Obs	1603	135			1603	135			1603	135	1603	135

In Table 14, column I provides the estimated unconditional mean for the six series over the sample and FMD periods. All series have a very small positive average daily return except for the Devro firm, and all series have smaller returns over the FMD period compared with those over the sample period. The differences of the daily returns of the six series between the non-FMD and FMD periods are -0.3969%, -0.32% , 0.008%, -0.164%, 0.019%, and -0.406%, respectively, indicating that there are large decreases over the FMD period for the whole market (FTSE 100 and FTSE 250) and individual meat-product companies (Devro).

The entries in column II are the Wilcoxon-Mann-Whitney test for the difference of mean of return over the FMD vs. non-FMD periods. For the FTSE 100, the P-value is 0.25, suggesting that we cannot reject the null hypothesis that the two means are equal. Similarly, for the six series, only for the FTSE 250, the means over the non-FMD period are significantly greater than over the FMD period.

Column III provides the estimated unconditional volatility. Over the sample period, the individual food companies have the highest volatility, then the food product and retail industry, while the whole stock market index is the lowest, which may imply that the food industry has relatively higher unconditional volatility regardless of the FMD event. The difference of the annual unconditional volatilities of the six series between the FMD and non-FMD periods are 5.55%, 2.69%, 0.47%, 0.317%, -5.08%, and 4.76%, respectively, indicating that there are large increases over the FMD period on the whole market (FTSE 100 and FTSE 250) and meat-product firms (Devro), and slightly higher increases for the food product and retail industry, although with a large decrease for non-meat-product firms.

Column IV is the F-test for the difference of variance of the return over the FMD vs. the non-FMD period. For the FTSE 100, the P-value is less than 0.0001, suggesting that

we can reject the null hypothesis that the two variances are equal; further, it suggests that unconditional volatility over the FMD period is significantly greater than over the non-FMD period. Similarly, the unconditional volatility of the FTSE 250 and meat-product firms over the FMD period are significantly greatly than over the non-FMD period, while an F-statistic of 0.663 and a P-value of 0.001 for non-meat-product companies indicate that the unconditional volatility of non-meat-product firms is significant lower over the non-FMD period than over the FMD period.

In general, Table 14 indicates that FMD did have an impact on both the unconditional mean and volatility of the six series-more or less. The largest effect seems to be a negative impact on unconditional mean for the small capitalization market (FTSE 250), while for others its impact is relatively smaller, and insignificant. It also has a larger positive and statistically significant impact on unconditional volatility for the whole market and meat-product firms.

The negative skewness coefficients of the FTSE 100, the FTSE 250, and food product indexes provided in column IV indicate that the return distribution is substantially negatively skewed (mean less than median), implying more excess negative return than excess positive return, while the others have slightly positive skewness, indicating more extreme positive return (Fig. 21). Compared with the estimated skewness coefficients over the non-FMD period, the estimated skewness coefficients over the FMD period are ”more negatively” skewed for the whole market and for individual food product companies, indicating more excess negative return over the FMD period, while they are ”more positively” skewed for the food product and retail industry.

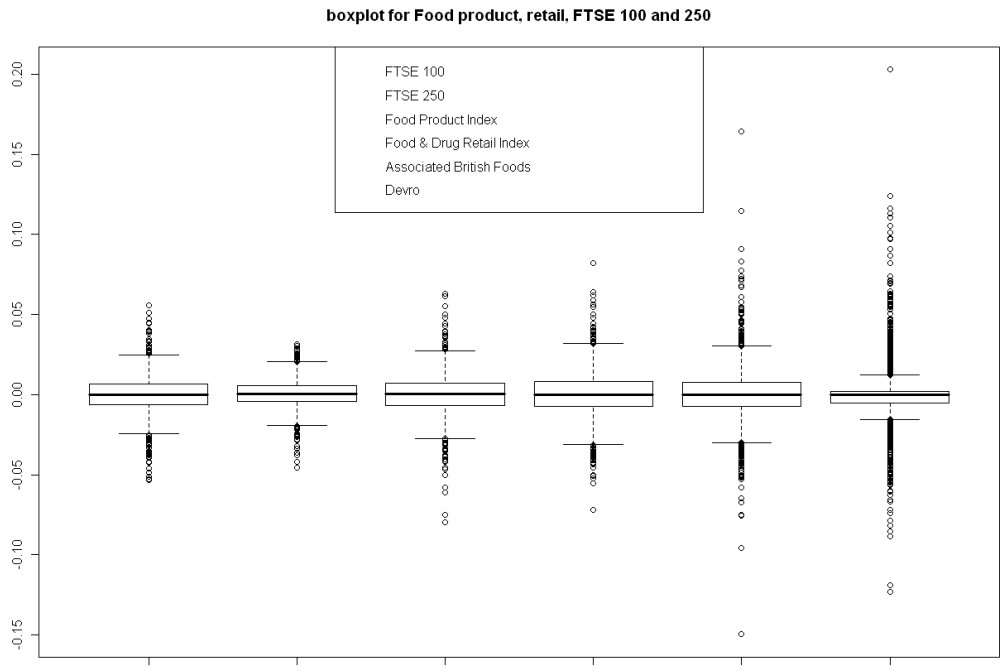


Figure 21: Box-plot for Six Series

The kurtosis coefficient is a measure of the thickness of the tails of the distribution. Compared with the estimated kurtosis coefficients over the non-FMD period, the estimated kurtosis coefficients over the FMD period are ”more thin” for FTSE 100, the food product industry, and individual food product companies, indicating less excess return over the FMD period, while more for FTSE 250 and the food retail industry. Additionally, all have heavy tails and skewness (Fig. 21), implying excess return and risk. Those suggest that a GARCH-M model is needed to capture both the skewness and the high kurtosis.

In general, although the volatility of FTSE 100 and meat products is higher over the FMD period, their excess return is less, implying market price fluctuation is relative large but within a limited range. Both volatility and excess return for non-meat-product firms are less over the FMD period, implying that non-meat-product firms are less affected, even ”better off” to some extent, which may result from the food substitution effect.

4.3.2 GARCH Analysis and Structure Break

An analysis of the correlation of the returns, presented in Fig. 22, indicates only weak dependence in the FTSE 250, the individual firm’s return. The correlation of the squared returns (Fig. 23), however, indicates substantial dependence in the volatility of returns and implies a GARCH analysis. As discussed above, the GARCH (1,1) is a popular, and the most robust, member of the family of volatility models. Thus, we first will fit those six series into the GARCH (1,1).

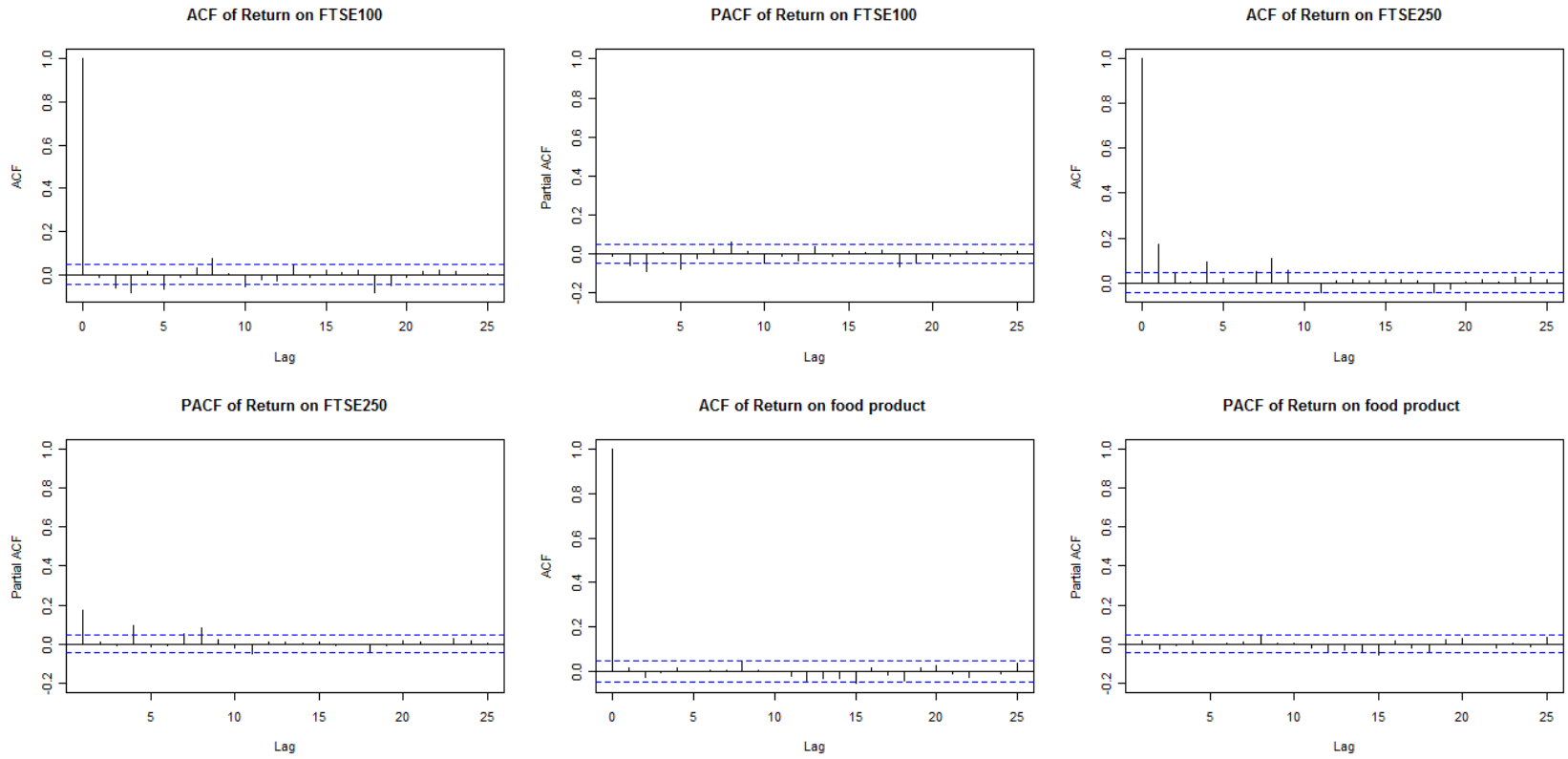


Figure 22: ACF and PACF Test for Daily Return

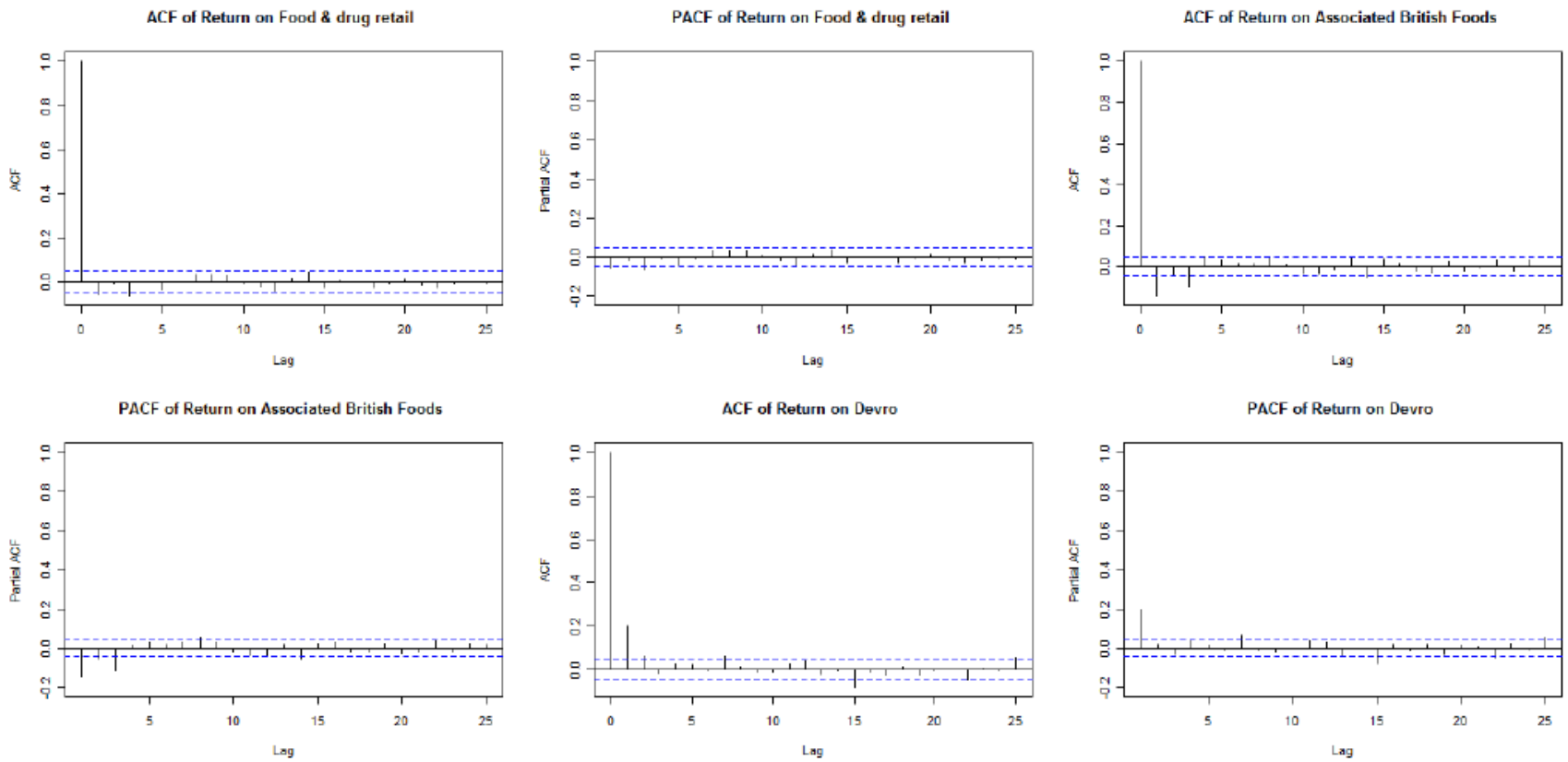


Figure 22: Continued

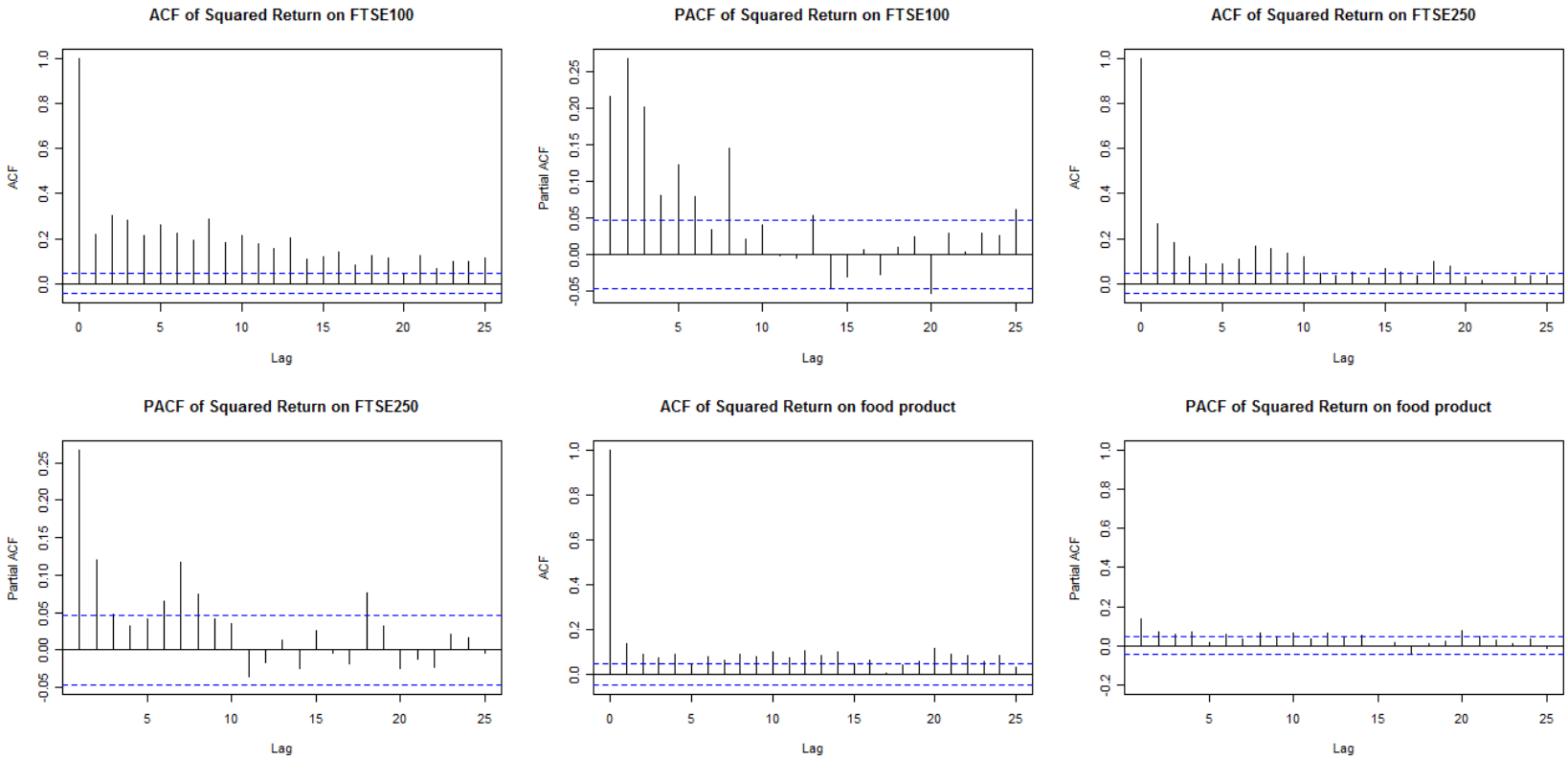


Figure 23: ACF and PACF Test for Squared Return

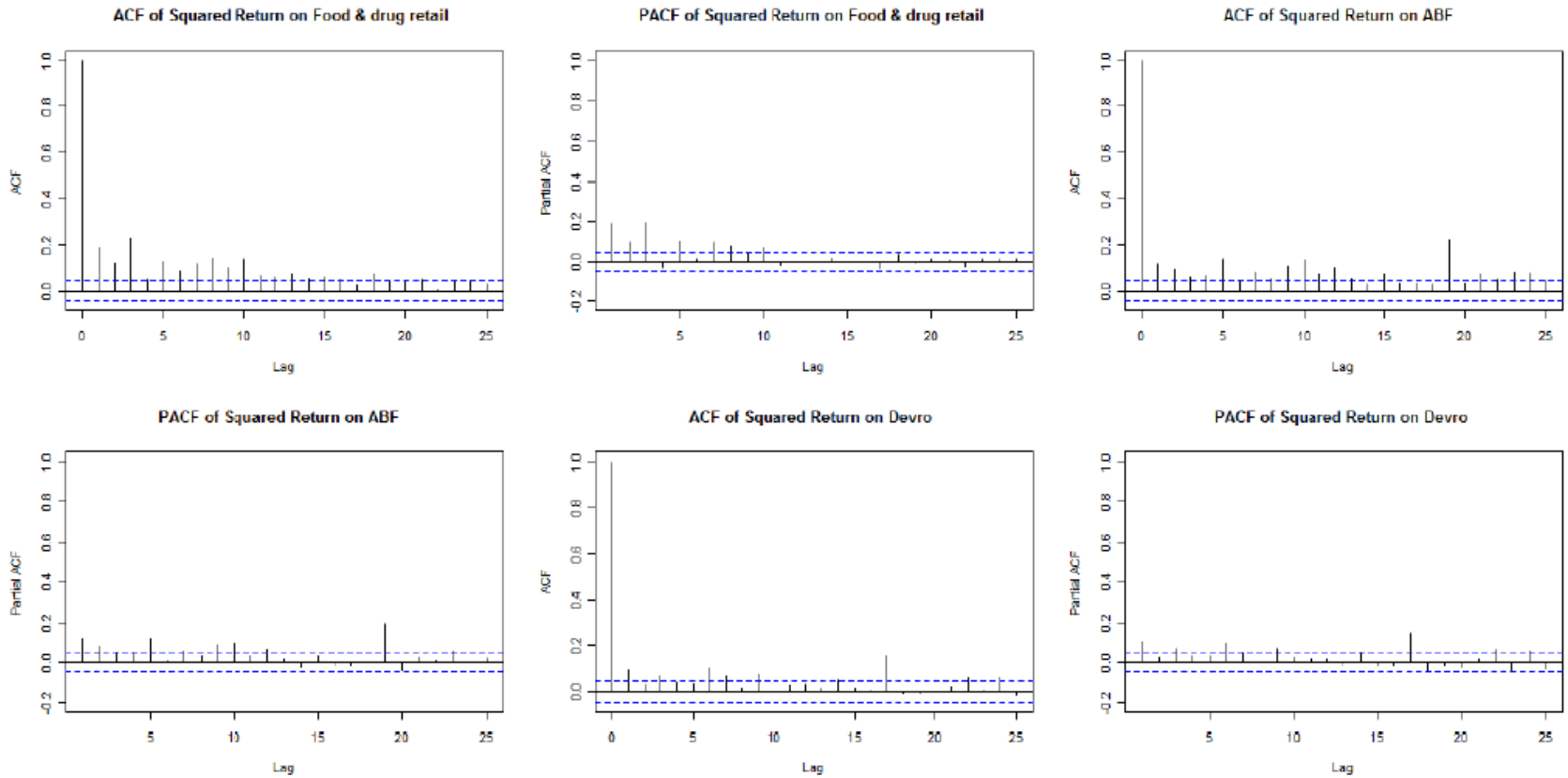


Figure 23: Continued

The parameter estimates for those six series are presented in Table 15. The P-values of LM test statistics for all series are larger than 10%, suggesting that we cannot reject the null hypothesis of no ARCH errors and the goodness of fit of the models. The unconditional variance of the GARCH (1,1) process is calculated as $\sigma^2 = \omega(1 - \alpha - \beta)^{-1}$. For example, using the estimated parameters ω, α and β, the estimated unconditional volatility of the FTSE 100 over the sample period is 0.0113, which is very close to the 0.0115 of the sample unconditional volatility (Table 1). Similarly, the others also are very close to the sample unconditional volatility (Rows VII and VIII), indicating that the GARCH (1,1) model is fitted well. Table 14 also provides estimated conditional volatility over the sample and the FMD period. The conditional volatility over the FMD period is much higher than that the over the period for the large-capitalization stock market (FTSE 100) and meat-product firm (Devro). For the small-capitalization stock market (FTSE 250), the estimated conditional volatility over the FMD period is 0.00835, slightly higher than that over the sample period, 0.00807.

Table 15: Parameter Estimate for Six Series

	FTSE 100		FTSE 250		Food Product		Food Retail		ABF		Devro	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	4.11E-04	0.058	7.57E-04	$< .0001$	4.48E-04	0.0798	0.05962	5.96E-02	0.0006	0.030	3.31E-04	0.393
ω	1.95E-06	0.005	4.50E-06	$< .0001$	1.31E-06	0.0116	5.10E-06	0.0040	4.00E-07	0.0252	6.41E-06	$< .0001$
α	0.08622	$< .0001$	0.1078	$< .0001$	0.04749	$< .0001$	0.072	$< .0001$	0.031	$< .0001$	0.054	$< .0001$
β	0.8986	$< .0001$	0.8283	$< .0001$	0.9447	$< .0001$	0.9009	$< .0001$	0.967	$< .0001$	0.931	$< .0001$
LM TEST	12.86	0.379	17.10	0.145	2.99	0.995	16.455	0.171	8.227	0.767	14.403	0.275
$\hat{UV}^*$	0.0113		0.00839		0.0129		0.0138		0.0147		0.0210	
Sample UV	0.0115		0.0084		0.0124		0.014		0.0176		0.0196	
$\hat{CV}^*(Sample)$	0.0108		0.00807		0.0120		0.0135		0.0160		0.0187	
$\hat{CV}(FMD)$	0.0130		0.00835		0.0118		0.0134		0.0151		0.0218	

Note:
$\hat{UV}$ is the estimated Unconditional Volatility from summary statistics
$\hat{CV}$ is the estimated conditional Volatility from GARCH(1,1) model

The conditional volatility over the FMD period is slightly lower than that over the sample period for food products, the food and drug retail industry, as well as Associated British Foods, a non-meat-product firm.

Figure 24 plots the estimated conditional volatility of the GARCH (1,1) model for six markets. It also shows that the FMD event had different effects on those markets. For whole market and meat-product firms, its effect is relatively larger than average conditional volatility (red dashed lines), implying that the market and investors indeed ”fear,” while for the food products and retail industry, as well as the non-meat-product companies, its impact is relatively smaller, and investors feel less stressful.

Figure 25 plots real return and 95% conditional predicted intervals over the FMD period, which are computed by equation $95\%CI = \mu \pm 1.96 \times \sqrt{h_t}$. It shows that there are few real return jumps outside predicted intervals-for example, in FTSE 100, FTSE 250, and the Devro firm-and thus there is the possibility of structure change.

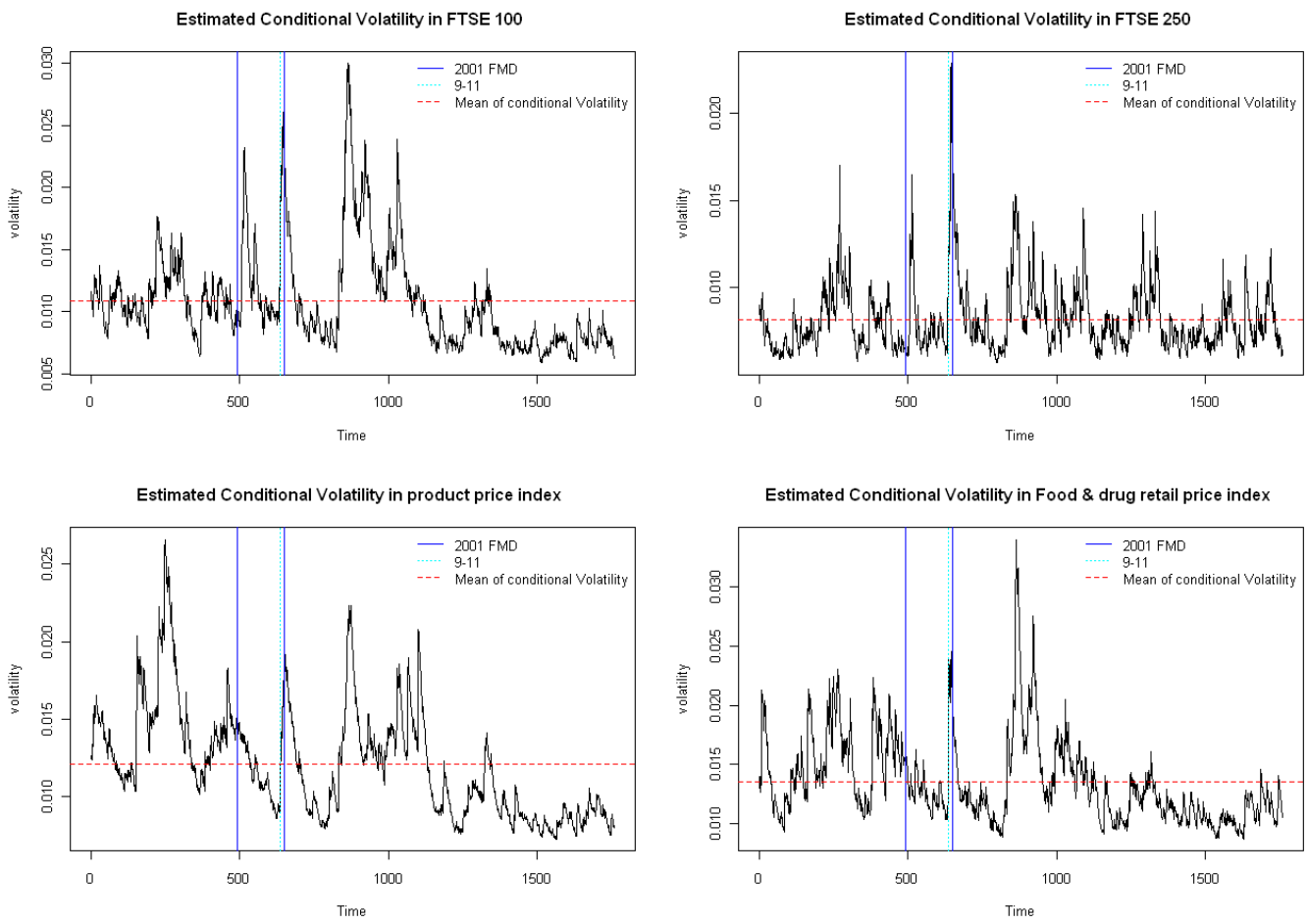
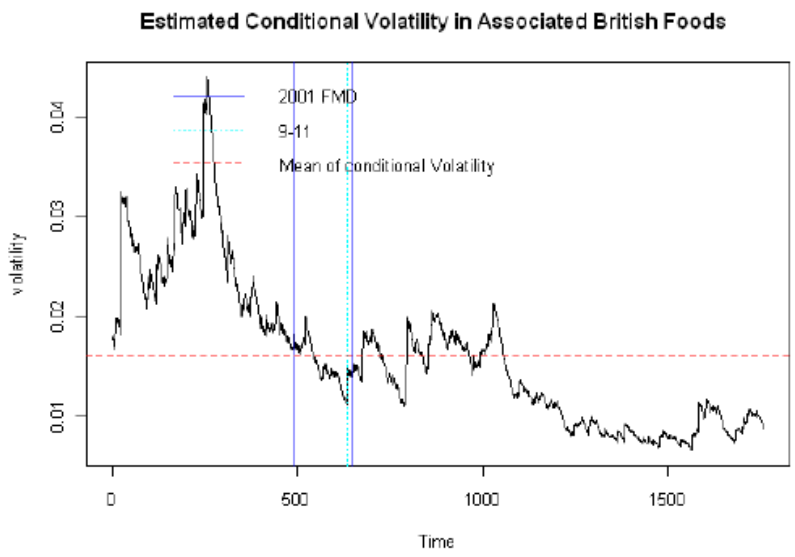


Figure 24: Estimate Conditional Volatility for Six Series



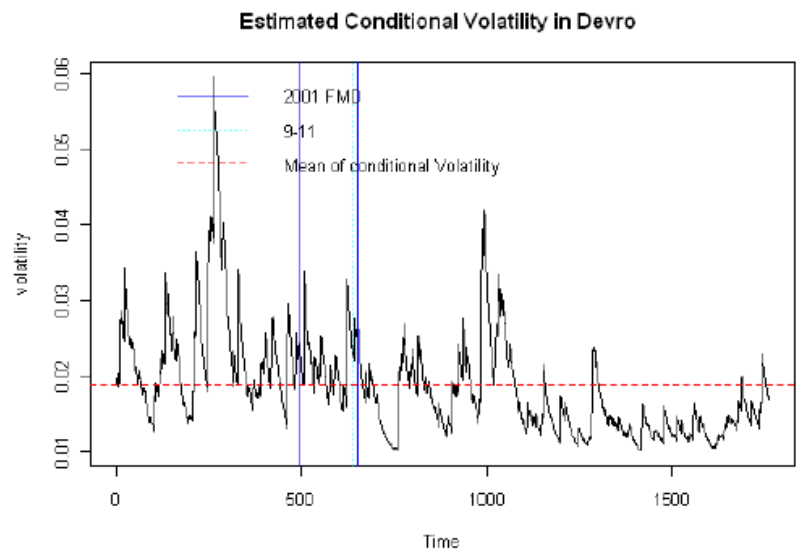


Figure 24: Continued

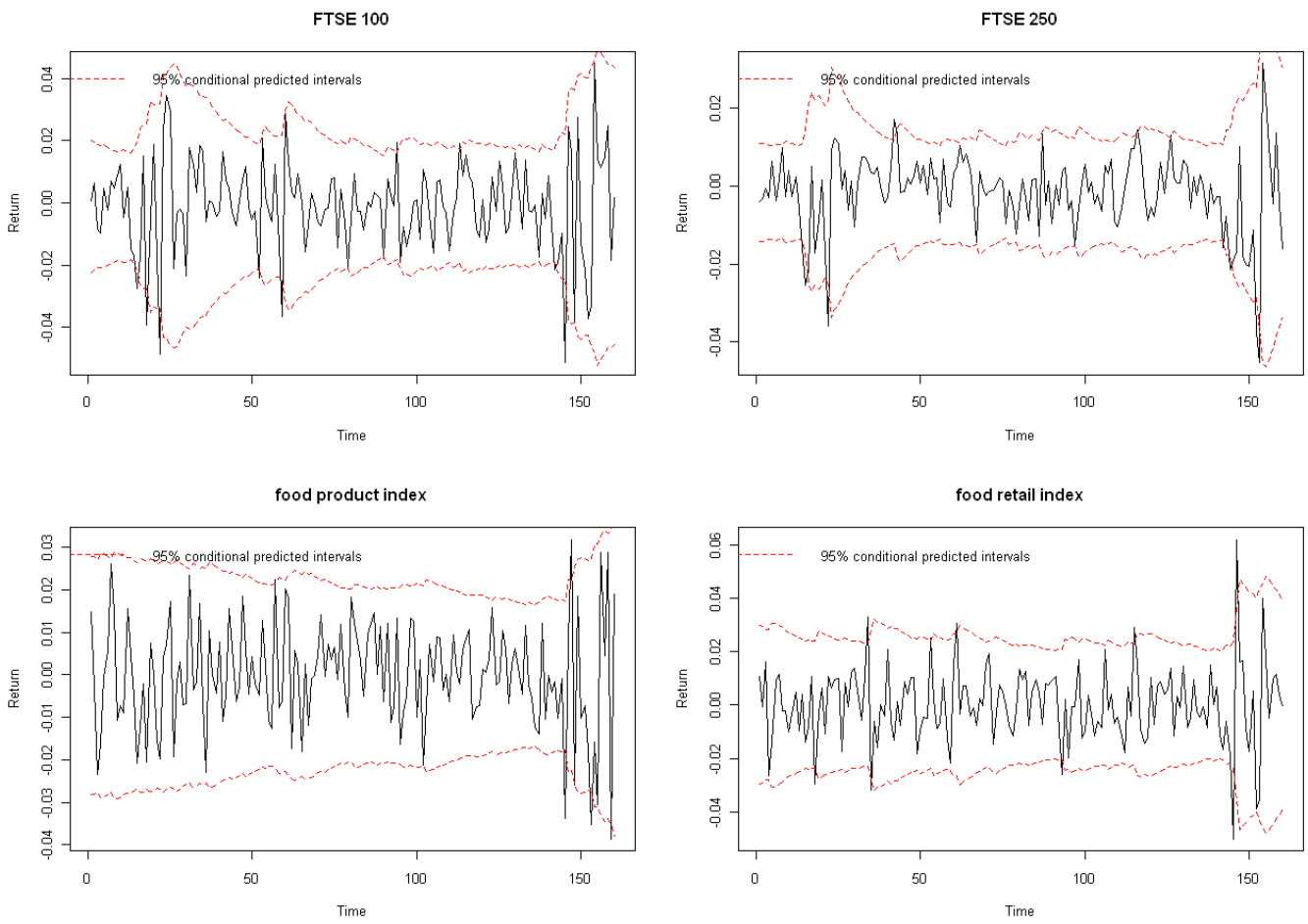


Figure 25: Real Return and 95% Conditional Predicted Intervals over FMD Period

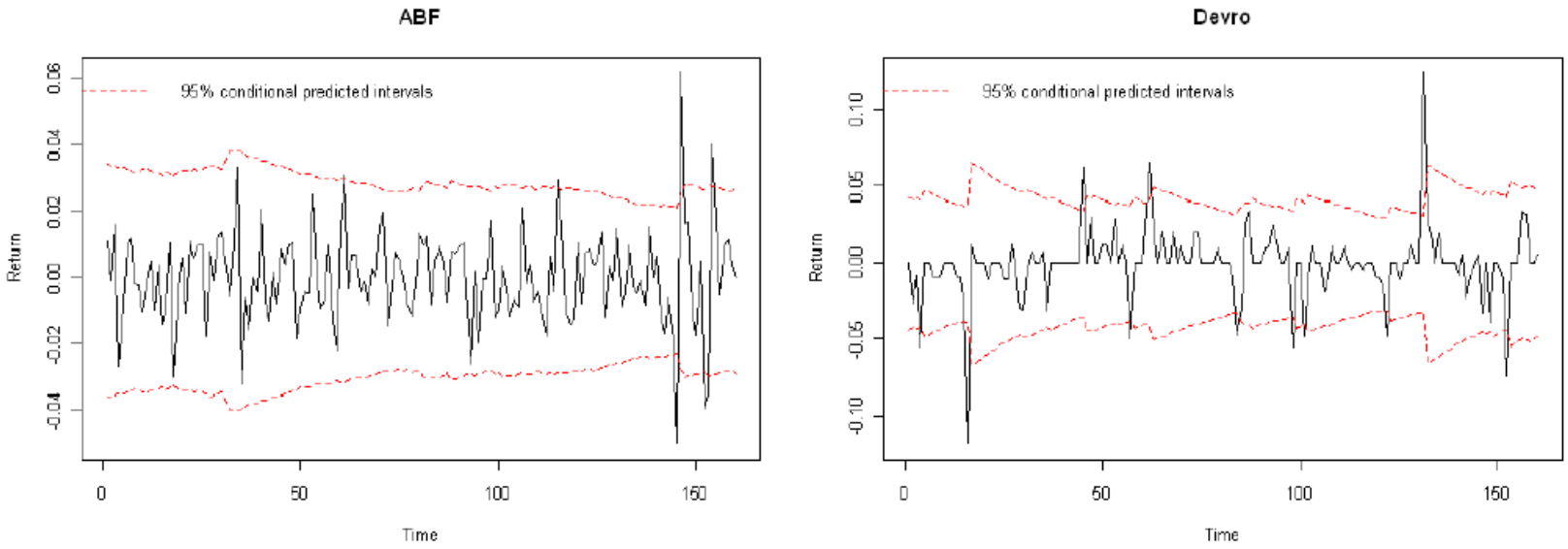


Figure 25: Continued

Table 16: Chow Test for Structure Change

Break points	23 March 2001		11 Sept. 2001	
	F-stat.	P-value	F-stat.	P-value
FTSE100	1.27	0.2592	1.92	0.1660
FTSE250	0.92	0.3388	2.10	0.1473
Food product	0.89	0.3458	0.46	0.4965
Food retail	0.01	0.9394	0.00	0.9465
ABF	0.05	0.8269	0.26	0.6133
Devro	8.48	0.0036	5.19	0.0229

A Chow test was provided in Table 16 to test structure change at the break point on March 23, 2001, when the number of confirmed cases jumped up to 40 and last three days and 11 Sept. 2001, 9-11 event. We also tested before and after 10 days of the specific day (March 23, 2001), but the value of the F-statistic is the largest on that day. Thus, we chose it as the structure break point.

In Table 16, there is a structure break only on meat-product firms. Although the Chow test is also statistically significant at the 9-11 point, the significance may be caused by FMD events. We also tested before and after 10 days of the specific day (9/11/2001), but the value of the F-Statistic is not the largest on the 9/11 event point.

4.3.3 GARCH-M Estimate

Our objective is to measure the different impacts of the FMD event on the volatility of different markets. As discussed above, GARCH (1,1) is fitted well, and other information sets include the number of confirmed cases, the time period of the FMD outbreak, and the 9/11 event. Those suggest that we can use a variety of modified GARCH (1,1)-in-mean models.

Table 17 presents the estimates for Model 1 through Model 4 for the FTSE 100 index.

Comparing Model 2 with Model 1, the value of the LRT test statistic is 17.48. Under the null hypothesis that Model 1 is correctly specified, this test statistic should be asymptotically distributed as an χ_1^2 random variable. Thus, we can reject the null hypothesis at the 10% level. A smaller AIC value for Model 2 also suggests that Model 2 should be better fitted. Similarly, Model 3 and Model 4 are better fitted compared with Model 1 by both the LRT test and the AIC criterion. For comparison of Model 2 and Model 3, the only criterion used is AIC, which shows that Model 2 with smaller AIC (-10974.44) is better. The result for comparison of Model 2 and Model 4 is a little confusing. The LRT test statistic is 2.45, referring to χ_1^2, and we cannot reject the null hypothesis that Model 4 is significantly better than Model 2 at the 5% level. However, the AIC from Model 4 is -10974.90, slightly smaller than that from Model 2, with -10974.44 of AIC. Finally, we use Model 2 to fit the FTSE 100 series because it had a better estimate on the mean equation. Similarly, the other series were estimated, and the results are provided in Tables 18- 22. We apply Model 2 to FTSE 250, food products, the food and drug retail index, and the Associated British Foods firm series, and Model 3 to the Devro firm series.

Table 17: Exogenous Variables Selection for FEST 100

	Model 1		Model 2		Model 3		Model 4	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.00033	0.67	0.00042	0.59	0.00038	0.63	0.0004	0.58
FMDT	-0.0018	0.023	-0.0021	0.010	-0.00175	0.11	-0.0019	0.052
ω	1.6E-06	0.002	1.6E-06	0.0017	1.7E-06	0.0015	1.7E-06	0.001
α	0.081	$< .0001$	0.078	$< .0001$	0.0767	$< .0001$	0.0732	$< .0001$
β	0.905	$< .0001$	0.912	$< .0001$	0.9068	$< .0001$	0.909	$< .0001$
δ	0.0195	0.81	0.0093	0.91	0.0141	0.87	0.0081	0.92
Dcase	4.0E-06	0.0275	4.40E-06	0.0072	6.4E-06	0.013	5.5E-06	0.013
S11			0.00058	0.21			0.00058	0.24
FMDT					4.2E-06	0.011	2.2E-06	0.211
Log likelihood	5486.48		5495.22		5490.04		5496.45	
AICc	-10958.96		-10974.44		-10964.09		**-10974.90**	
SIC	-10920.73		**-10930.75**		-10920.39		-10925.75	
HQIC	-10944.82		**-10958.28**		-10947.92		-10956.72	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 18: Exogenous Variables Selection for FEST 250

	Model 1		Model 2		Model 3		Model 4	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.0011	0.268	0.0012	0.233	0.00118	0.25	0.0013	0.21
FMDT	-0.0013	0.051	-0.0013	0.041	-0.0013	0.091	-0.0013	0.074
ω	3.82E-06	0.0001	3.1E-06	0.0002	3.4E-06	0.0002	3.0E-06	0.0003
α	0.098	$< .0001$	0.076	$< .0001$	0.094	$< .0001$	0.075	$< .0001$
β	0.847	$< .0001$	0.87	$< .0001$	0.855	$< .0001$	0.878	$< .0001$
δ	-0.037	0.77	-0.059	0.66	-0.041	0.75	-0.0639	0.64
Dcase	7.8E-07	0.18	1.1E-06	0.031	1.1E-06	0.12	1.3E-06	0.032
Sept11			0.000572	0.19			5.5E-04	0.20
FMDT					9.8E-07	0.35	5.6E-07	0.503
Log likelihood	5917.43		5921.75		5917.85		5921.96	
AICc	-11820.86		**-11827.52**		-11819.7		-11825.93	
SIC	-11782.63		**-11783.81**		-11776.01		-11776.77	
HQIC	-11806.72		**-11811.34**		-11803.54		-11807.74	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 19: Exogenous Variables Selection for Food Product Index

	Model 1		Model 2		Model 3		Model 4	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.0013	0.19	0.0012	0.23	0.0013	0.19	1.3E-03	0.16
FMDT	-0.000074	0.93	-0.0013	0.04	-0.000072	0.94	-1.5E-04	0.88
ω	1.3E-06	0.0004	3.1E-06	0.0002	1.2E-06	0.0004	1.2E-06	0.0004
α	0.0487	$< .0001$	0.076	$< .0001$	0.048	$< .0001$	0.045	$< .0001$
β	0.943	$< .0001$	0.875	$< .0001$	0.944	$< .0001$	.943	$< .0001$
δ	-0.081	0.37	-0.059	0.66	-0.080	0.37	-8.8E-02	0.33
Dcase	8.0E-23	1	1.1E-06	0.031	4.0E-24	1	3.7E-07	0.88
Sept11			0.00057	0.19			0.00032	0.16
FMDT					3.8E-07	0.60	3.6E-23	1
Log likelihood	5264.93		5273.21		5265.04		5273.21	
AICc	-10517.86		**-10530.43**		-10516.08		-10530.43	
SIC	-10477.63		**-10486.73**		-10470.39		-10479.27	
HQIC	-10501.72		**-10514.26**		-10497.92		-10510.24	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 20: Exogenous Variables Selection for Food & Drug Retail Index

	Model 1		Model 2		Model 3		Model 4	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.00069	0.61	0.00078	0.56	0.00069	0.61	0.00078	0.56
FMDT	-0.00022	0.82	-5.5E-04	0.59	-2.7E-04	0.80	-5.5E-04	0.59
ω	5.35E-06	$< .0001$	4.94E-06	$< .0001$	5.1E-06	$< .0001$	4.9E-06	$< .0001$
α	0.076	$< .0001$	0.070	$< .0001$	0.075	$< .0001$	0.070	$< .0001$
β	0.89	$< .0001$	0.903	$< .0001$	0.898	$< .0001$	0.903	$< .0001$
δ	-0.010	0.92	-1.7E-02	0.87	-9.5E-03	0.92	-1.7E-02	0.87
Dcase	-1.2E-22	1	8.6E-07	0.79	-4.5E-23	1	8.6E-07	0.79
Sept11			0.00063	0.11			0.00063	0.11
FMDT					1.7E-06	0.27	-3.5E-23	1
Log likelihood	5051.22		5059.39		5051.65		5059.39	
AICc	-10088.37		**-10102.69**		-10087.21		-10100.67	
SIC	-10050.21		**-10059.09**		-10043.61		-10051.63	
HQIC	-10074.30		**-10086.62**		-10071.14		-10082.60	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 21: Exogenous Variables Selection for Associated British Foods

	Model 1		Model 2		Model 3		Model 4	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.0011	0.082	0.00113	0.07	0.0011	0.07	0.0011	0.07
FMDT	-0.00079	0.47	-6.1E-04	0.61	-7.4E-04	0.55	-6.1E-04	0.62
ω	4.0E-07	0.003	4.0E-07	0.002	4.2E-07	0.002	3.9E-07	0.002
α	0.034	$< .0001$	0.033	$< .0001$	0.034	$< .0001$	0.033	$< .0001$
β	0.964	$< .0001$	0.964	$< .0001$	0.963	$< .0001$	0.964	$< .0001$
δ	-0.039	0.45	-4.0E-02	0.44	-3.9E-02	0.45	-4.1E-02	0.43
Dcase	5.3E-06	0.045	6.8E-06	0.0087	8.8E-06	0.030	6.8E-06	0.07
Sept11			0.00027	0.02			0.00027	0.03
FMDT					1.5E-06	0.080	-6.2E-24	1
Log likelihood	4869.84		4876.96		4870.98		4876.96	
AICc	-9725.69		**-9737.92**		-9725.97		-9737.92	
SIC	-9687.45		**-9694.23**		-9682.27		-9686.77	
HQIC	-9711.54		**-9721.76**		-9709.80		-9717.74	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 22: Exogenous Variables Selection for Devro

	Model 1		Model 2		Model 3		Model 4	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.00094	0.42	0.00095	0.42	-0.000739	0.52	-0.0010	0.37
FMDT	0.0019	0.01	2.1E-03	0.003	7.3E-04	0.78	1.0E-03	0.68
ω	6.2E-06	$< .0001$	6.6E-06	$< .0001$	0.000031	$< .0001$	0.000030	$< .0001$
α	0.055	$< .0001$	0.057	$< .0001$	0.149	$< .0001$	0.145	$< .0001$
β	0.931	$< .0001$	0.928	$< .0001$	0.772	$< .0001$	0.775	$< .0001$
δ	-0.011	0.86	-1.3E-02	0.85	7.5E-02	0.26	9.5E-02	0.16
Dcase	3.2E-06	0.018	3.3E-06	0.016	0.000036	$< .0001$	3.6E-05	$< .0001$
Sept11			0.000238	0.30			0.000099	0.89
FMDT					0.000083	$< .0001$	0.0000803	$< .0001$
Log likelihood	4524.57		4524.90		4549.37		4547.19	
AIC	-9035.15		-9033.81		**-9082.74**		-9076.38	
SIC	-8996.91		-8990.11		**-9039.05**		-9027.23	
HQIC	-9021.00		-9017.64		**-9066.58**		-9058.20	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 23: Parameter Estimate for Six Series

	FTSE 100		FTSE 250		Food product		Food retail		ABF		Devro	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Constant	0.00042	0.597	0.0012	0.233	0.0013	0.162	0.00078	0.562	0.0011	0.074	-0.000739	0.5259
FMDT	-0.0021	0.010	-0.0013	0.0417	-0.000152	0.88	-0.00055	0.5987	-0.000614	0.6112	7.38E-04	0.781
ω	1.6E-06	0.0017	3.1E-06	0.0002	1.2E-06	0.0004	4.9E-06	$< .0001$	4.0E-07	0.0026	0.0000311	$< .0001$
α	0.0728	$< .0001$	0.0764	$< .0001$	0.0456	$< .0001$	0.0702	$< .0001$	0.0338	$< .0001$	0.1494	$< .0001$
β	0.912	$< .0001$	0.875	$< .0001$	0.946	$< .0001$	0.903	$< .0001$	0.964	$< .0001$	0.7723	$< .0001$
δ	0.009361	0.913	-0.0599	0.668	-0.0881	0.33	-0.017	0.87	-0.04	0.44	7.55E-02	0.2664
Dcase	4.4E-06	0.0072	1.1E-06	0.0317	3.75E-07	0.87	8.6E-07	0.7954	6.89E-06	0.0087	3.6E-05	$< .0001$
Sept11	0.000589	0.2127	0.000572	0.195	0.000321	0.1623	0.000639	0.1157	0.000276	0.0294	-	-
FMDT	-	-	-	-	-	-	-	-	-	-	8.36E-05	$< .0001$

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.

δ is the direction and strength of the risk-return relationship.

Dcase is the first difference of scheduled announcement of the number of confirmed cases.

Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

The models with best-fitted estimate for each series are summarized in Table 23. For the FTSE 100, the best-fitted model is estimated in Eq. 4.13. The estimated coefficient over the FMD period ($FMDT_t$) in the mean equation is 0.0021, lower than that over the non-FMD period, and it is statistically significant. The estimated coefficient of $\sqrt{h_t}$ is 0.00936, indicating a positive relationship between return and risk (volatility) but not statistical significance. The estimated coefficient of ARCH terms (h_{t-1}^2) is 0.0728, slightly lower than that estimated in the GARCH (1,1) model, 0.0862, and it is statistically significant by Wilcoxon-Mann-Whitney test with equal variance, while for the GARCH terms (ε_{t-1}^2) is 0.912, slightly higher than that estimated in the GARCH (1,1) model, 0.8986. The estimated $\alpha + \beta$ in both the GARCH (1,1) and GARCH (1,1)-M models is not significantly different from unity by one side Wilcoxon-Mann-Whitney test, which implies that the integrated GARCH (volatility persistence) and volatility structure are unchanged. The estimated coefficient of the difference of the number of daily cases (Dcase) is 0.0000044, which is statistically significant at the 1% level, implying that the average marginal impact on daily volatility is 0.0021(=$\sqrt{.0000044}$=.21%), or about 3.3% annual volatility. This indicates that when increase 1 the first difference of confirmed case, which will increase 3.3% annual volatility on average.

$$\begin{aligned} R_t &= .00042 - 0.0021FMDT_t^{**} + .00936\sqrt{h_t} + \varepsilon_t \\ h_t &= .0000016 + 0.0728\varepsilon_{t-1}^{2***} + 0.912h_{t-1}^{***} + .0000044Dcase_t^{**} + .000589S11_t \end{aligned} \tag{4.12}$$

For the FTSE 250, the best-fitted model is estimated in Eq. 4.13. The estimated coefficient of over the FMD period ($FMDT_t$) is -0.0013, and it is statistically significant, indicating that it is 0.0013 lower than that over the other period on daily return. The estimated coefficient of $\sqrt{h_t}$,-0.0599 indicates a negative relationship between return and risk

but not statistical significance. The estimated coefficient of ARCH terms (ε_{t-1}^2) is 0.0764, slightly lower than that estimated in the GARCH (1,1) model, 0.1078, and it is statistically significant, while the GARCH term (h_{t-1}^2) is 0.875, slightly higher than that estimated in the GARCH(1,1) model, 0.8283,. The estimated coefficient of the difference of the number of daily cases (Dcase) is 0.000001, and it is statistically significant at the 5% level. The average marginal impact on daily volatility is 0.001(0.1%), about 1.58% annual volatility, indicating that when increase 1 the first difference of confirmed case, which will increase 1.58% annual volatility at average.

$$\begin{aligned} R_t &= .0012 - 0.0013FMDT_t^* + -.0599\sqrt{h_t} + \varepsilon_t \\ h_t &= .0000031^{***} + 0.0764\varepsilon_{t-1}^{2***} + 0.875h_{t-1}^{***} + .000001Dcase_t^* + .000572S11_t \end{aligned} \tag{4.13}$$

Similarly, for both the food-product (Eq. 4.14) and food retail indexes (Eq. 4.15), the estimated coefficients from the GARCH (1,1)-M model of Dcase show a positive impact on volatility but not a significant one, and $FMDT_t$ is negative but not statistically significant. The estimated coefficients of α , β and $\alpha + \beta$ are not significantly different for the two models, implying no significant impact of FMD on the whole food product and retail industry.

$$\begin{aligned} R_t &= 0.0013 - 0.000152FMDT_t + -.0811\sqrt{h_t} + \varepsilon_t \\ h_t &= .0000012^{***} + 0.0456\varepsilon_{t-1}^{2***} + 0.946h_{t-1}^{***} + .00000037Dcase_t + .000321S11_t \end{aligned} \tag{4.14}$$

$$\begin{aligned} R_t &= 0.00078 - 0.00055FMDT_t + -0.017\sqrt{h_t} + \varepsilon_t \\ h_t &= .0000049^{***} + 0.0702\varepsilon_{t-1}^{2***} + 0.9036h_{t-1}^{***} + .00000086Dcase_t + 0.000639S11_t \end{aligned} \tag{4.15}$$

For non-meat product firms (ABF), the best-fitted model is estimated in Eq. 4.16. The

estimated coefficient over the FMD period ($FMDT_t$) is -0.000614 in the mean equation, but it is not statistically significant. The estimated coefficient of $\sqrt{h_t}$, -0.04, indicates a negative relationship between return and risk but not a statistically significant one. The estimated coefficient of the ARCH terms is 0.0338, slightly higher than that estimated in the GARCH (1,1) model, 0.031, and it is statistically significant, while the GARCH term is 0.964, slightly lower than that estimated in the GARCH (1,1) model, 0.967. Estimated $\alpha + \beta$ in both the GARCH (1,1) and GARCH (1,1)-M models is not significantly different from unity, indicating integrated GARCH (volatility persistence) and volatility structure unchanged. The estimated coefficient of the difference of the number of daily cases (Dcase) is 0.00000689, which is statistically significant at the 1% level. The average marginal impact on daily volatility is 0.0026 (0.25%) , or about 4.17% annual volatility.

$$R_t = 0.0011 - 0.000614FMDT_t - .04\sqrt{h_t} + \varepsilon_t$$
$$h_t = .0000004^{***} + 0.0338\varepsilon_{t-1}^{2***} + 0.964h_{t-1}^{***} + .00000689Dcase_t^{**} + 0.000276S11_t^{*} \tag{4.16}$$

For Devro, a meat-product firm, the best-fitted model is estimated in Eq. 4.17.From this model, daily return over the FMD period ($FMDT_t$) is 0.000738, but it is not statistically significant. The estimated coefficient of $\sqrt{h_t}$ is .00936, indicating a positive relationship between return and risk (volatility), but it is not statistically significant. The estimated coefficient of ARCH terms is 0.149, much higher than that estimated in the GARCH (1,1) model, 0.054, and the difference is statistically significant, while the estimated coefficient of GARCH terms is 0.772, much lower than that estimated in the GARCH (1,1) model, 0.931. The estimated $\alpha + \beta$ in both GARCH (1,1) and GARCH is not significantly different from unity, which implies an integrated GARCH (volatility persistence), but in the GARCH (1,1)-M model $\alpha + \beta$ is significantly different from unity, implying a volatility

structure change after the introduction of exogenous variables. The estimated coefficient of the difference of the number of daily cases (Dcase) is 0.000036, which is statistically significant at the 0.1% level. The average marginal impact on daily volatility is 0.006 (0.6%), about 9.5% annual volatility, indicating that when increase 1 confirmed case, which will increase 9.5% annual volatility at average and over the FMD period, the conditional volatility is statistically significantly 14.51% higher than that over the non-FMD period at annual volatility.

$$R_t = -0.000739 + 0.000738FMDT_t - .0755\sqrt{h_t} + \varepsilon_t$$

$$h_t = .0000311^{***} + 0.149\varepsilon_{t-1}^{2***} + 0.772h_{t-1}^{***} + .000036Dcase_t^{***} + 0.0000836FMDT_t^{***} \tag{4.17}$$

4.3.4 Robustness

We assess the model's stability by a rolling analysis. We used a different rolling window with the same length-for example, rolling forward 100, 200, 300, and 400 observations, then comparing the estimated coefficients with those from the original sample. Tables 24 through 29 provide the comparison between the original sample and rolling forward 100 to 400 observations for the six series. From Table 24, the coefficient of FMDT is relatively stable, with a range from -0.0021 to -0.0024, implying that the returns over the FMD period are indeed lower than those over the non-FMD period, regardless of the sample selection for the FTSE 100. The estimated coefficient of first difference of the number of confirmed cases, also relatively stable, ranged from 3.81 $\times 10^{-6}$ to 4.4 $\times 10^{-6}$, implying that the Dcase indeed impact the conditional volatility, while the estimated coefficients of ARCH and GARCH are very stable. This indicates the stability of the volatility construct. Also, for other series, the estimated constructs are very stable.

Similarly, for FTSE 250, the returns over the FMD period are lower than over the non-FMD period, regardless of the sample section, but the impact of first difference of the confirmed case on conditional volatility does vary with sample selection at a significant level. Hence, it is not certain if it has impact on conditional volatility. Tables 28 and 29 show that the Dcase does impact the conditional volatility for both non-meat-product firms (ABF) and meat-product firms (Devro). For meat products, the conditional volatility over the FMD period is higher than over the non-FMD period.

Table 24: Robustness Check for FTSE 100

	Original Sample		Rolling 100		Rolling 200		Rolling 300		Rolling 400	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Cons.(10^{-4})	4.2	0.59	5.5	0.49	5.44	0.48	7.76	0.29	6.54	0.37
FMDT (10^{-3})	-2.1	0.01	-2.16	0.0087	-2.2	0.0072	-2.33	0.0037	-2.43	0.0023
$\omega(10^{-6})$	1.6	0.0017	1.82	0.0008	1.88	0.0006	2.00	0.0001	2.01	0.0001
α	0.072	$< .0001$	0.073	$< .0001$	0.08	$< .0001$	0.084	$< .0001$	0.086	$< .0001$
β	0.91	$< .0001$	0.91	$< .0001$	0.90	$< .0001$	0.89	$< .0001$	0.89	$< .0001$
$\delta(10^{-3})$	9.36	0.91	3.5	0.96	6.94	0.93	-3.218	0.96	17.7	0.83
Dcase (10^{-6})	4.40	0.0072	4.33	0.008	4.19	0.014	3.94	0.02	3.81	0.03
Sept11 (10^{-4})	5.89	0.21	6.08	0.22	6.42	0.25	6.88	0.28	7.02	0.29
Obs.	1738		1738		1738		1738		1738	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 25: Robustness Check for FTSE 250

	Original Sample		Rolling 100		Rolling 200		Rolling 300		Rolling 400	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Cons.(10^{-4})	.12	0.23	1.61	0.18	1.18	0.24	1.39	0.16	1.25	0.22
FMDT (10^{-3})	-1.3	0.04	-1.39	0.06	-1.46	0.04	-1.61	0.02	-1.16	0.03
$\omega(10^{-6})$	3.10	0.0002	4.91	0.0001	4.21	$< .0001$	5.07	$< .0001$	5.16	$< .0001$
α	0.076	$< .0001$	0.089	$< .0001$	0.092	$< .0001$	0.10	$< .0001$	0.095	$< .0001$
β	0.87	$< .0001$	0.84	$< .0001$	0.85	$< .0001$	0.82	$< .0001$	0.83	$< .0001$
$\delta(10^{-3})$	-59.9	0.66	-91.7	0.544	-30.6	0.80	-35.1	0.77	-15.9	0.89
Dcase (10^{-6})	1.10	0.031	.95	0.10	.95	0.10	.703	0.26	.825	0.18
Sept11 (10^{-4})	5.72	0.19	7.17	0.21	6.05	0.24	7.06	0.25	6.93	0.24
Obs.	1738		1738		1738		1738		1738	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.

δ is the direction and strength of the risk-return relationship.

Dcase is the first difference of scheduled announcement of the number of confirmed cases.

Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 26: Robustness Check for Food Product

	Original Sample		Rolling 100		Rolling 200		Rolling 300		Rolling 400	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Cons.(10^{-4})	1.3	0.16	1.28	0.17	1.17	0.21	1.674	0.10	1.41	0.16
FMDT (10^{-3})	-1.52	0.88	-1.35	0.89	-1.84	0.85	-1.87	0.84	-3.33	0.72
$\omega(10^{-6})$	1.20	0.0004	1.08	0.0006	1.44	0.0001	1.36	0.0001	1.60	$< .0001$
α	0.04	$< .0001$	0.043	$< .0001$	0.054	$< .0001$	0.045	$< .0001$	0.05	$< .0001$
β	0.87	$< .0001$	0.84	$< .0001$	0.85	$< .0001$	0.82	$< .0001$	0.83	$< .0001$
$\delta(10^{-3})$	-88.1	0.33	-81.3	0.35	-62.7	0.49	-112.0	0.28	-72.4	0.49
Dcase (10^{-6})	.37	0.87	.38	0.86	.09	0.96	.191	0.93	.48	0.98
Sept11 (10^{-4})	3.21	0.16	3.0	0.1458	3.79	0.21	3.53	0.16	3.96	0.20
Obs.	1738		1738		1738		1738		1738	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 27: Robustness Check for Food Retail

	Original Sample		Rolling 100		Rolling 200		Rolling 300		Rolling 400	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Cons.(10^{-4})	7.8	0.56	10.2	0.43	12.94	0.31	20.2	0.13	23.43	0.07
FMDT (10^{-3})	-0.55	0.59	-5.77	0.57	-6.81	0.50	-7.46	0.45	-7.21	0.45
$\omega(10^{-6})$	4.90	0.0001	4.04	$< .0001$	4.17	$< .0001$	5.37	$< .0001$	5.01	$< .0001$
α	0.07	$< .0001$	0.06	$< .0001$	0.06	$< .0001$	0.07	$< .0001$	0.06	$< .0001$
β	0.90	$< .0001$	0.91	$< .0001$	0.90	$< .0001$	0.89	$< .0001$	0.89	$< .0001$
$\delta(10^{-3})$	-17.0	0.87	-34.6	0.74	-48.5	0.64	-100.	0.36	-132.9	0.24
Dcase (10^{-6})	86.0	0.79	1.01	0.74	91.7	0.76	59.1	0.84	61.6	0.83
Sept11 (10^{-4})	6.39	0.11	5.94	0.091	6.13	0.09	7.1	0.12	7.0	0.11
Obs.	1738		1738		1738		1738		1738	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 28: Robustness Check for ABF

	Original Sample		Rolling 100		Rolling 200		Rolling 300		Rolling 400	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Cons.(10^{-4})	11	0.074	5.79	0.45	2.94	0.70	5.74	0.53	-0.44	0.96
FMDT (10^{-3})	-0.61	0.61	-65.3	0.59	-1.01	0.36	-0.55	0.65	-1.147	0.27
$\omega(10^{-6})$	40.0	0.0026	66.1	$< .0001$	1.64	$< .0001$	61.8	$< .0001$	3.12	$< .0001$
α	0.03	$< .0001$	0.02	$< .0001$	0.05	$< .0001$	0.02	$< .0001$	0.06	$< .0001$
β	0.96	$< .0001$	0.97	$< .0001$	0.93	$< .0001$	0.97	$< .0001$	0.91	$< .0001$
$\delta(10^{-3})$	-40	0.44	3.79	0.95	39.5	0.57	-2.358	0.97	71.4	0.43
Dcase (10^{-6})	6.89	0.008	6.83	0.007	6.18	0.03	6.29	0.008	5.27	0.07
Sept11 (10^{-4})	2.76	0.02	2.7	0.02	3.0	0.08	2.80	0.01	4.13	0.13
Obs.	1738		1738		1738		1738		1738	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.
δ is the direction and strength of the risk-return relationship.
Dcase is the first difference of scheduled announcement of the number of confirmed cases.
Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

Table 29: Robustness Check for Devro

	Original Sample		Rolling 100		Rolling 200		Rolling 300		Rolling 400	
Model	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value	Coef.	P-Value
Cons.(10^{-4})	-7.39	0.52	-2.26	0.85	-31.96	0.0093	.846	0.84	1.86	0.92
FMDT(10^{-3})	.738	0.78	0.22	0.92	-3.55	0.16	-0.08	0.96	-0.195	0.94
$\omega(10^{-6})$	31.1	$< .0001$	36.5	$< .0001$	52.7	$< .0001$	41.3	$< .0001$	43.6	$< .0001$
α	0.14	$< .0001$	0.15	$< .0001$	0.21	$< .0001$	0.13	$< .0001$	0.15	$< .0001$
β	0.77	$< .0001$	0.75	$< .0001$	0.65	$< .0001$	0.74	.	0.71	$< .0001$
$\delta(10^{-3})$	75.5	0.2664	48.2	0.5118	23.09	0.0012	36.2	.	15.9	0.894
Dcase (10^{-6})	36.0	$< .0001$	35.3	$< .0001$	34.5	0.0014	35.3	$< .0001$	36.0	$< .0001$
FMDT(10^{-5})	8.36	$< .0001$	8.38	$< .0001$	11.4	$< .0001$	9.07	.	9.95	$< .0001$
Obs.	1738		1738		1738		1738		1738	

Note: FMDT is the indicator variables, which are 1 if during the FMD outbreak and otherwise 0.

δ is the direction and strength of the risk-return relationship

Dcase is the first difference of scheduled announcement of the number of confirmed cases.

Sept11 is the indicator variables, which is 1 if time is September 11, 2001 and otherwise 0.

4.4 Summary

From summary statistics Table 14, we found that the unconditional mean of daily return had a larger decrease for whole markets represented by the FTSE 100 and the FTSE 250 and individual food-product companies, represented by Associated British Foods and Devro, compared with the sample period from Apr. 1999 to Dec. 2005. The unconditional volatility had a larger increase for whole markets and individual food product firms associated with meat products, while for the whole food product and retail industry, the unconditional volatility is unchanged, even decreased for non-meat-product firms.

From the GARCH (1,1)-M model and rolling window model, we found that the mean of return over the FMD period is significantly lower than that over the non-FMD period for the whole stock market represented by the FTSE 100 and the FTSE 250, but not significantly different for the food product and retail industry and food-product companies. We also found that the conditional volatilities over the FMD period are much higher than those over the sample period for the large-capitalization stock market (FTSE 100) and Devro, which is associated with meat products. For the small-capitalization stock market, the estimated conditional volatility over the FMD period is slightly higher, while it is slightly lower for food products, the food and drug retail industry, as well as Associated British Foods (non-meat products). The announcement of the confirmed cases had an impact on the large-capitalization market and the food-product firm, and it had the largest marginal impact on meat products. With an estimated coefficient of 0.000036, it indicated when increase 1 confirmed case, the annual volatility will increase at 9.5%, while for non-meat product and large capitalization market; they are estimated as 4.1% and 3.3%, respectively, given the original sample.

Another finding is that the FMD does not have significant impact on the whole food product and retail industry but does have an impact on whole markets, the reason being that on the one hand, although meat-product companies are hit badly, for non-meat-product firms (e.g., Associated British Foods) the impact is small and not significant-even unconditional and conditional volatility are lower over the FMD period. On the other hand, the FMD hit badly not only the meat-product companies but also insurance and tourism companies, and the whole market index includes those firms.

Our results have important implications for index investing and option pricing. The index investing approach is generally considered a passive strategy. However, our results suggest that major events may lead to volatility shifts and may alter the risk-return trade-off. So it may be prudent for investors to revisit the composition of a portfolio consisting of index funds, particularly after major events. Policymakers may consider a temporary restriction on short selling to reduce market over-reaction by providing a cooling off period.

CHAPTER V

CONCLUSIONS

5.1 Conclusions

Several topics in the field of bio-security are discussed in this dissertation.

In Chapter II, we used a Poisson regression model with adjustment dispersion associated with random simulation results from an AusSpead model to estimate the parameters of the model given one location as the start point in the simulation, and we predicted the probability/risk and expected cattle loss of FMD outbreak spreading to the premises, given others as start points under different scenarios in the study area. Results show that cattle numbers have a positive effect on probability of being infected, while distance between start point and a given premises has a negative effect. Under different scenarios, the impact of cattle number is slightly different, but distance has a similar negative impact on the number of events under the four different scenarios. That is, when the distance between a premises and an outbreak point is shorter than 20 miles, the ”marginal” impact of distance will rise steeply when the distance decreases, while if the distance between a premises and an outbreak point is longer than 20 miles, an increase or decrease in distance will not impact the probability. Since distance plays an important role in predicting event probability, as return, identifying high-risk areas depends on the spatial distributions of premises, and high density of premises usually has high probability of transmission of the virus or becoming infected. The total expected cattle loss plays an important role in decision making. When FMD disease hits large premises-for example, large feedlots or large beef-a large cattle loss

will occur. Based on the AusSpead simulation model, our estimation and prediction show that large cattle loss was concentrated in three counties-Deaf Smith, Parmer, and Castro-and those results were from approximately 70% feedlots with over 10,000 cattle located in the counties. When an FMD virus is introduced into a backyard, the expected loss is about 88,000 head, while when an FMD virus is introduced into large or small feedlots or large beef the loss is approximately double that number. Losses in the three counties are 141, 137, and 150 thousand head, respectively.

In Chapter III, we first tested the best mitigation strategies with average minimum animal loss by the Tukey test, and the results showed that the best mitigation strategies for all four scenarios are strategies 1, 5, 9, 10, and 15. Then we used one of the best strategies, strategy 15, with the ”worst” or largest animal loss to estimate costs of disposing of animal carcasses and transportation under four different scenarios and examined the effectiveness of disposal strategies. The results show that the estimated average highest disposal cost is under scenario 2, while the lowest is under scenario 4, because it had the largest-scale carcass disposal when lower-cost disposal methods are exhausted, resulting in the need for higher-cost disposal methods. Thus, the unit disposal cost will vary with carcass scale. The unit transportation cost also varies by the distributions of the infected premises and disposal locations. The estimated unit transportation cost is lower under scenarios 1 and 4 and higher under scenarios 2 and 3 because under scenarios 2 and 3 the infected premises are more highly concentrated, which causes less-optimal transportation options for the infected premises.

In Chapter IV, we found that the mean of return over the FMD period is significantly lower than that over the non-FMD period on the whole stock market, represented by the FTSE 100 and the FTSE 250, but not significantly different for the food product and retail

industry and food product companies. We also found that the conditional volatility over the FMD period is much higher than that over the sample period for the large-capitalization stock market (FTSE 100) and Devro, which is associated with meat products. For the small-capitalization stock market (FTSE 250), the estimated conditional volatility over the FMD period is slightly higher, while it is slightly lower for food products, the food and drug retail industry, as well as Associated British Foods (non-meat products). The announcement of the confirmed cases had an impact on the large-capitalization market and food-product firms, and it had the largest marginal impact on meat products. With an estimated coefficient of .000036, it indicated when increase 1 confirmed case relatively yesterday, the annual volatility will increase by 9.5%, while for non-meat products and the large-capitalization market they are estimated as 4.1% and 3.3%, respectively, given the original sample. Another finding is that the FMD does not have significant impact on the whole food product and retail industry but does have an impact on the whole markets, the reason being that on the one hand, although meat product companies are hit badly, for non-meat-product firms-for example, Associated British Foods-the impact is small and not significant, and even unconditional and conditional volatilities are lower over the FMD period. On the other hand, the FMD hit badly not only the meat product companies but also insurance and tourism companies, which are included in the whole market index. Our results have important implications for index investing and option pricing. The index investing approach is generally considered a passive strategy. However, our results suggest that major events may lead to volatility shifts and may alter the risk-return trade-off. So it may be prudent for investors to revisit the composition of a portfolio consisting of index funds, and policymakers may consider a temporary restriction on short selling to reduce market overreaction, particularly after major events.

5.2 Limitations and Future Research

In Chapter II there is a relatively large prediction error because some factors like animal transportation, temperature, and wind cannot be included in the model. The estimated probability is a conditional probability, and further research may focus on estimating the probability to introduce a virus such that a complete decision can be made. The number of research studies on individual firms is relatively small, so future research will undoubtedly collect more food-product firm data and focus on policy discussion of short, temporary restrictions to stabilize volatility after a major event such as an FMD outbreak.

REFERENCES

Bollerslev, T. 1986. “Generalized autoregressive conditional heteroskedasticity”. *Journal of Econometrics* 31: 307–327.

Ekboir J. 1999. “Potential impact of foot-and-mouth disease in California: the role and contribution of animal health surveillance and monitoring services.” Agricultural Issues Center, Division of Agriculture and Natural Resource, University of California, Davis, CA, 123 pp.

Ellis, D. 2006. “Emergency management of mass animal mortality.” Paper presented at Texas animal health commission, 13 November.

Engle, R. F and Andrew, P. 2001. “What good is a volatility model?” *Quantative Finance* 1: 237–245.

Engle, R. F. 1982. “Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation.” *Econometrica* 50: 987–1007.

Engle, R. F. and Bollerslev, T. 1986. “Modelling the persistence of conditional variances.” *Econometric Reviews* 5: 1–50.

Engle, R. F., Lilien, D., and Robins, R. 1987. “Estimation of time varying risk premia in the term structure: the arch-m model.” *Econometrica* 55: 391–407.

Garner, M. and Beckett, S. 2005. “Modeling the spread of foot-and-mouth disease in Australia.” *Australian Veterinary Journal* 83: 758–766.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. 1993. “On the relation between the expected value and the volatility of the nominal excess returns on stocks.” *Journal of Finance* 48: 1779–1801.

McCauley, E., New, J., Aulaqi, N., Sundquist, W., and Miller, W. 1979. “A study of the

potential economic impact of foot-and-mouth disease in the United States." Washington, D.C.: Government Printing Office

Mukhtar, S., Boadu, F. O., Jin., Y. H., Shim.,W. B., Vestal, T. A., andWilson, C. L. 2008. "Managing contaminated animal and plant materials-field guide on best Practices." Department of Homeland Security Press. Forthcoming

Nelson, D. b. 1990. "Stationary and persistence in the garch(1, 1) model." *Econometric Theory* 6: 318–334.

Paarlberg, P. L.and Lee, J. G. and Seitzinger, A. H. 2002. "Potential revenue impact of an outbreak of foot and mouth disease in the United States." *Journal of the American Veterinary Medical Association* 20: 988–992.

Rich, K. M. and Winter-Nelson, A. 2007. "An integrated epidemiological-economic Analysis of foot and mouth disease: Applications to the southern cone of South America." *American Journal of Agricultural Economics* 89: 682–697.

Waller, L. A. and Gotway, C. A. 2004. "Applied Spatial Statistics for Public Health Data." Hoboken, New Jersey: Wiley.

Ward, M., Norby, B., McCarl, B., Elbakidze, L., Srinivasan, R., Highfield, L., Loneragan, S., and Jacobs, J. 2004. "The high plains project report." Texas A& M University.

Wolfinger, R. D. and O'Connell, M. 1993. "Generalized linear mixed models: a pseudolikelihood approach." *Journal of Statistical Computing and Simulation* 48: 233–243.

Yang, P., Chu, R., and Chung, W.B.and Sung, H. 1997. "Epidemiological characteristics and financial costs of the 1997 foot-and-mouth disease epidemic in Taiwan." V*eterinary Record* 145: 731–734.

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