# Three Essays in Natural Risks and Environmental Policy Analysis

by

Sheng Li

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Approved by

Denis Nadolnyak, Chair, Associate Professor of Agricultural Economics and Rural Sociology
Yaoqi Zhang, Co-chair, Professor of Forestry Economics
Valentina Hartarska, Professor of Agricultural Economics and Rural Sociology
Diane Hite, Professor of Agricultural Economics and Rural Sociology

## Abstract

This dissertation includes three essays that address economic impacts of natural risks and environmental policy on natural resources and economic development. Chapter 1 examines the impacts of economic and flood risk factors on agricultural land conversion in a coastal area by employing an interval censored survival model. Results suggest that flood and hurricane risks affect conversion timing controlling for exogenous and endogenous economic and demographic factors and for spatial interdependence. Alternative model specifications that include parametric, interval censored, and frailty models show remarkably similar results. The flood risk slows down farmland conversion in high risk areas and the impact is especially pronounced after a major hurricane event. Conversion is more likely in areas where flood risk is small relative to the amenity value of the property. Locational attributes, proxies for farming profitability, and local and national economic indicators have expected signs and magnitudes. These findings should be helpful in land use policy development and design.

Chapter 2 explores how the regional social vulnerability contributes to the distribution of the impacts of Hurricane Katrina across income communities on the Gulf of Mexico. A potential relationship between location-based social vulnerability and post-disaster impacts including estimated damage, migration, and recovered cost in the U.S is explored. Base on this, I develop a regional index of social vulnerability and examine how its various dimensions are related to heterogonous damages from the hurricane. Results show a significantly positive relationship between social vulnerability and post-disaster damage estimates and highlight the importance of

spatial attributes of the affected areas. Alternative social indexes are suggested that are more sensitive to the post-damage impacts in the low and median income groups.

Chapter 3 employs the Equilibrium Displacement Models (EDM) to explore the distribution of welfare gains between farmers, fertilizer suppliers, and other sectors that result from a fertilizer subsidy policy that increased the subsidies by 670% since 2004 in China. The Muth model is extended and applied to the Chinese rice industry to estimate the relative incidence and distribution of welfare among different sectors. It is found that the total benefits from the policy are about RMB 7.7 billion yuans. The fertilizer suppliers gain about RMB 51 billion yuans from the favorable policy with mean subsidy incidence 0.8 and capturing about 70% of total surplus. The results suggest that transferring parts of subsidies to the non-fertilizer sectors could be considered an efficient way to redistribute welfare in different sectors.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

| | |
|---|---|
| CRTS | Constant Returns to Scale |
| DC | Drainage Class |
| EDM | Equilibrium Displacement Models |
| FC | Farmland Classification |
| FEMA | Federal Emergency Management Agency |
| FGDL | Geographic Data Library |
| FLP | Forest Legacy Programs |
| FSP | Forest Stewardship Programs |
| HPI | Housing Price Index |
| LCC | Land Capability Class |
| LCPA | Lee County Property Appraiser |
| NOAA | National Oceanic and Atmospheric Administration |
| SFWMD | South Florida Water Management District |
| SHFA | State Housing Finance Agency |
| SOVI | Social Vulnerability Index |
| USGS | United States Geological Survey |

# Chapter 1

## 1. Introduction

As land becomes increasingly scarce and valuable for economic development, agricultural land is gradually converted to non-farm uses. For example, between 1982 and 2002, total cropland in the 50 United States including land in conservation programs declined by 6% or 27 million acres (Lubowski et al, 2008). The conversion is particularly pronounced in coastal areas where urban sprawl is rapidly replacing prime agricultural land to meet the pressures of population growth and the increasing demand for development. In the past few decades, the coastal regions saw many inundations whose impacts were aggravated by the intense urbanization of flood prone areas, which led to loss of human lives and financial damages (Wagner et. al., 2009).

Consequently, there is an increased interest in evaluating the impacts of natural risks on land conversion and in the design of land use related policies in coastal areas, particularly those that are in high demand for residential purposes. Significant local efforts have been made and federal policies and regulations have been developed to mitigate flood hazards and control economic development in flood-prone areas. Various policy instruments (e.g., compensatory payments, disaster relief subsidies, and catastrophic insurance) are employed to control land use patterns and conversion dynamics (Botzen et al., 2009).

The objective of this study is to estimate how flood risks in coastal areas impact agricultural land conversion to residential and commercial uses. Particular emphasis is placed on the evaluation of the impacts of exogenous risk factors on land use change in a dynamic setting (timing of conversion). Duration analysis is employed to estimate the impacts of natural hazards on the timing of agricultural land conversion in a coastal area in Florida. The analysis also controls for location-specific and socio-economic parcel attributes and macroeconomic indicators. The empirical model also accommodates endogeneity and spatial interdependence. Finally, we compare conversion patterns of cropland, forestland, and rangeland.

A number of studies on the drivers of land conversion during the last decade indicate that net returns to alternative land uses are the major factor that determines land use change (Irwin et al. 2002, 2007; Bell et al., 2000). In a coastal area, land use change is also driven by the differences in expected losses from natural disasters (hazards) in different land uses (Bin et al., 2006). Thus, land values and conversion dynamics are largely determined both by rent capitalization and by potential losses from natural disasters.

Existing studies focus on estimation of the impacts of climate and environmental factors on land use change. For example, Brath et al. (2006) assesses the impacts of flood frequency on land use change in a river basin. Tollan et al. (2002) analyses the relationship between flood frequency and land cover. Bin et al. (2008) estimates the effects of flood hazards on housing prices in a coastal area. Less attention is paid to the impact of natural disasters on agricultural land conversion and even fewer studies directly estimate the relationship between natural disasters and land conversion dynamics. The next section builds a theoretical framework of land conversion probability as a function of natural risks and other factors. Section 3 describes the empirical model. Section 4 describes the data. Estimation results are discussed in Section 5.

## 2. Theoretical Framework

Land use and land cover change have attracted interest among a wide variety of researchers who have been modeling spatial and temporal patterns of land conversion in order to understand its causes and consequences (Mertens et al., 1997). Geographers, engineers, and other hard scientists have succeeded in developing successful spatial models of land use change at highly disaggregate scales, whereas less attention has been paid to the economic and behavioral components underlying land use change (Irwin and Geoghegan, 2001).

Economic models of land use change focus on explaining the causal relationships between individual choices and land use change outcomes. The focus is on individual owners' land use decisions governed either by maximization of expected returns or utility derived from the land (Irwin et al., 2001, 2003, 2007). In case of the former, landowners' decisions on whether and when to convert are based on maximization of the net present value (NPV) of returns from land. The decision to convert emphasizes an individual's choice in a static setting, while the timing of conversion incorporates future (expected) changes in demand, supply, and productivity as well as the option value of not converting (Bell et. al., 2006). A number of authors have extended the basic theory to empirical studies, including land's locational attributes and soil quality as fundamental elements in the agricultural land conversion decisions (Plantinga et al., 1996; Miller et al., 1999). In reality, however, landowners are heterogeneous and have different reservation values/opportunity costs. As Irwin and Geoghegan (2001) state, "*some owners may be especially good at farming or may have high recreational and aesthetic values for their land; others may be near retirement and looking for a means to liquidate their assets. These idiosyncrasies will induce a distribution of unobservable factors, randomly distributed across the landscape that will, in turn, induce a distribution of optimal development times conditioned on explanatory variables*". These unobservable factors (such as risk perceptions, attachment values, life cycle, etc.) also affect conversion decisions.

The purpose of this study is to estimate how flood risks in coastal areas impact agricultural land conversion to residential and commercial uses. In addition to incorporating the common factors discussed above, we are particularly interested in examining the exogenous natural risk factors' impact on land use change in a dynamic setting (*when*, as opposed to just *whether*, to convert). The dynamics involve an individual landowner's optimal timing decision regarding the conversion of a land parcel from cropland, forestland, or rangeland to residential, commercial/service, or industrial uses.

Formally, following Irvin et al. (2002), conversion of parcel *i* from use *j* to use *k* at time *T* is a result of maximizing the net present value of returns from the parcel before and after time *T*:

(1) $$\max_T \int_0^T [R_{ij}(l,s,a,t) - \rho_{ij} L_{ij}] e^{-\delta t}\,\mathrm{dt} + \int_T^\infty [R_{ik}(l,s,a,t) - \rho_{ik} L_{ik}] e^{-\delta t} dt$$

The returns from the land before and after conversion at *T*, $R_{ij}(l,s,a,t)$ and $R_{ik}(l,s,a,t,T)$ , are functions of location (*l*), soil quality (*s*), and site attributes (*a*). $\rho_{ik} L_{ij}$ and $\rho_{ij}\ L_{ik}$ are expected flood related losses. $\rho_{ij}$and $\rho_{ik}$ are the probabilities of flood at location *i* and $L_{ij}$and $L_{ik}$ are the losses in land use *j* or *k* (before and after conversion). The first order condition with respect to conversion time *T* is:

(2) $$[R_{ijt}(l,s,a,T) - R_{ikt}(l,s,a,T)] e^{-\delta T} + \int_0^\infty \partial [R_{ik}(l,s,a,t,T) - \rho_{ik} L_{ik}] / \partial T e^{-\delta(t-T)} dt - [\rho_{ij} L_{ij}(l,s,a,T) - \rho_{ik} L_{ik}(l,s,a,T)] e^{-\delta T} = 0$$

where the first term in the parentheses is the condition of a simple static allocation model, the second term is the discounted value of changes in net return to use *k*, and the third term is the change in flood related losses. This suggests that the impact of flood probability on land conversion depends on the sign of $\rho_{ik} L_{ik}$-$\rho_{ij} L_{ij}$ .

## 3. A Hazard Model Application of the Timing of Land Conversion

Most of the traditional empirical studies of land conversion decisions use static empirical models. A common approach is to specify the development decision as a discrete choice (Bockstael et al., 2000; Brady et al., 2011). While this method is sufficient for estimating probabilities of conversion at certain time (parcel age), it relies on some restrictive assumptions (independence) and does not accommodate the dynamic nature of the process, which is important especially in fast developing areas where it is important to know when, rather than simply whether, a parcel is converted. Survival analysis is superior to logistic regression in that (1) it provides a distribution of probabilities rather than a probability for a certain duration, (2) accommodates censored observations, i.e., before all events are observed, (3) allows staggered entry of observation units (and back-and-forth conversion), and (4) utilizes more information on duration.

Duration (survival) models are widely used to analyze the timing of events in medical studies, finance, and have been applied in the economic literature on land conversion (Hartarska, 2005). In this study, a duration model is employed to analyze whether the differences in the expected losses from flood risk in different land uses affect the probability of land conversion. The timing of conversion is treated as a realization of a random process conditional on parcel attributes and flood risks. The probability of conversion of parcel $i$ in period $T$ can be expressed as

(3) $$h(t) = \lambda_0(t)\phi(\mathrm{X}, \beta)$$

where $\lambda_0(t)$ is the baseline hazard that describes the probability of failure (conversion), holding covariates constant, which may vary over time. $\phi(X,\beta)$ is a function of the covariates in $X$, where initially we consider only time-invariant regressors but later relax this assumption. The most common choice of $\phi(X,\beta)$ is the exponential form. Combining equations (1) and (2) in (3), the hazard function that incorporates the land conversion decision is specified as

$$(4) \qquad h(t) = \lambda_0(t) exp\{[R_{ijt}(l,s,a,T), R_{ik}(l,s,a,T), L_{ik}(l,s,a), L_{ij}(l,s,a);\ \rho_{ik}, \rho_{ij,}\beta\}$$

Empirically, the parameters in Equation 4 can be efficiently estimated using Maximum Likelihood in continuous time:

$$(5) \qquad \sum_1^N \{d_i \log[f(t_i|x_i,\theta) + (1-d_i)\log[1-F(t_i|x_i,\theta)]]\}$$

where $f(\cdot)$and $1-F(\cdot)$ are the density and cumulative of $t_i = t_i^*$ and $d_i$ is a censoring indicator.

The unbiased estimates require that outcomes are observed in continuous time. However, as mentioned by Wooldridge (2010), strictly continuous durations are rare in social science applications. Normally, the duration is only observed in discrete time periods corresponding to measurement/survey times. Wooldridge calls it grouped duration data while Lindsey et al. (2000) define it as time interval censored data. Earlier studies treat interval censored duration data as a sequence of binary outcomes. Wooldridge  defines it as a panel data set where each cross section observation is a vector of binary responses, along with covariates. The advantage of this approach is that it simplifies estimation of flexible hazard functions in a proportional hazard specification and incorporates time-varying covariates $\{(t_0, t_1), (t_1, t_2)\ldots(t_m, t_n)\ldots\}$.

Considering first the time-invariant covariates case, the proportional base hazard in Equation (4) for interval censored data is defined as

(6) $$\lambda(t; X, \beta) = \int_{t_{m-1}}^{t_m} \lambda_0(s)ds\, \phi(X, \beta)\,, \quad m = 1,2,3\ldots$$

Defining $d_i$ as a censoring indicator equal to one if duration *i* is uncensored, the log-likelihood for observation *i* can be written as

(7) $$\sum_{t=1}^{t-1} \log\left\{exp\left[-\int_{t_{m-1}}^{t_m}(\lambda(t; X, \beta))dt\right]\right\} + d_i \log\left\{1 - exp\left[-\int_{t_{m-1}}^{t_m}(\lambda(t; X, \beta))dt\right]\right\}$$

The log likelihood is more complicated with time-varying covariates, especially without assuming their strict exogeneity. If the covariates are constant within each time interval ($t_m$, $t_n$), the log likelihood is the same as in equation (7). Assuming that the hazard within interval *t* includes covariates that vary within intervals, the log likelihood for observation *i* can be written as

(8) $$\sum_{t=1}^{t-1} \log\left\{exp\left[-\int_{t_{m-1}}^{t_m}(\lambda(t; X_m, \beta))dt\right]\right\} + D_i \log\left\{1 - exp\left[-\int_{t_{m-1}}^{t_m}(\lambda(t; X_m, \beta))dt\right]\right\}$$

where $D_i$ is the censoring indicator*:*

(9) $D_i = D(T|T \geq t_{m-1}X_m,)$, m=1, 2, 3, 4.

An important step in evaluating the impact of natural hazards on land conversion decisions is specifying an appropriate baseline hazard and unobserved heterogeneity. There is no strong theoretical or empirical basis for assigning a particular functional form for the baseline hazard. Normally, Weibull, Exponential, and Log-normal functions can be implemented within this framework (Kim et al., 1997; Betensky et al., 2001). Unfortunately, there is no statistical test for selecting among the baseline hazard models because these models are not nested.

In the following empirical analysis, we use the interval censoring model to estimate how flood risks in coastal areas impact agricultural land conversion to residential and commercial uses. The baseline hazard is in parametric form which allows it to be monotonically increasing or decreasing in time (positive vs. negative duration dependence). We control for endogeneity of economic and spatial parcel attributes by estimating a system of equations in which the endogenous variables are co-determined with the conversion. We also accommodate spatial interdependence by introducing a spatial lag. For comparison purposes, a logit model, a parametric survival model, and semi-parametric approach (Cox proportional hazard model) are also estimated.

## 4. Data

For the analysis of the potential effects of flood risk on land conversion timing, we use a small scale dataset on land use change (conversion) in Lee County, Florida, during the period from 1974 to 2012. Lee County, located in Southwest Florida, contains the cities of Fort Myers and Cape Coral and is one of the fastest growing counties in the state that is under a relatively higher risk of natural disasters. Floods in this area occurred 275 times in the past 60 years, and almost half of parcels in the dataset are located in the high risk flood zones. Extreme climactic events such as hurricanes and storms are common in this area. The tornado index value there is also higher than the national level.

The land cover data for the analysis are collected from the South Florida Water Management District (SFWMD). This data set serves as documentation of land cover and land use within the District starting from 1974. However, the land cover data are not gathered annually but have been collected in 1974, 1988, 1995, 1999, 2004, 2008, and 2012. Land cover/land use in this dataset was photo interpreted on a 1:40,000 scale and classified using the SFWMD modified Florida Land Use and Cover Classification System (FLUCCS). The land parcels are mapped according to the land classification. The minimum mapping unit for parcels' classification was 2 acres for wetlands and 5 acres otherwise. Land features were stereoscopically interpreted from the aerial photography and vector data were compiled over corresponding USGS Digital Orthophoto Quadrangles (DOQ's). All the land cover data are combined into a cross section dataset by the ArcGIS based on spatial location. Land cover in 2012 is used as a base map and a total of 96,977 parcels are observed. The pooled data shows that, of the 352,100 acres that were in agricultural use in 1974, 188,000 acres (54.3%) were converted into developed uses by 2012 and only 12.7% of the parcels that were developed were converted back into forestland and rangeland. In addition, 36.2% of forested land and 41.8% of rangeland were developed by 2012.

Table 1.1 Land Transition Matrix by Area, Lee County, FL, 1974-2012, 1,000 acres.

| | Cropland | Forestland | Rangeland | Developed land | Other land | Total |
|---|---|---|---|---|---|---|
| Cropland | 26.4 | 89.9 | 22.2 | 188.0 | 25.6 | 352.1 |
| Forestland | 2.8 | 45.3 | 2.0 | 31.6 | 5.5 | 87.2 |
| Range land | 8.5 | 32.4 | 13.1 | 47.1 | 11.7 | 112.9 |
| Developed land | 0.7 | 6.4 | 1.3 | 75.5 | 2.7 | 86.5 |
| Other land | 0.5 | 0.1 | 0.1 | 1.6 | 1.2 | 3.5 |
| Total | 38.9 | 174.1 | 38.6 | 343.8 | 46.7 | 642.2 |

Table 1.2 Land Transition Matrix by Area, Lee County, FL, 1974-2012, % of total.

| | Cropland | Forestland | Rangeland | Developed land | Other land | Total |
|---|---|---|---|---|---|---|
| Cropland | 7.5% | 25.5% | 6.3% | 53.4% | 7.3% | 100% |
| Forestland | 3.2% | 52.0% | 2.2% | 36.2% | 6.3% | 100% |
| Range land | 7.5% | 28.7% | 11.6% | 41.8% | 10.4% | 100% |
| Developed land | 0.8% | 7.4% | 1.5% | 87.3% | 3.1% | 100% |
| Other land | 15.3% | 2.2% | 2.5% | 46.9% | 33.6% | 100% |

Flood risks zones are classified by using data from the Federal Emergency Management Agency (FEMA) on areas where the land is classified as Special Flood Hazard Area (SFHA). According to the FEMA, SFHAs are defined as areas that will be inundated by a flood event having a 1-percent (0.2-percent) chance of being equaled or exceeded in any given year. The 1-percent (0.2-percent) annual chance of flooding is also referred to as the base flood or 100-year (500-year) flood. Based on this definition, 9,900 acres in the 100-year floodplain (50.1% of the total in that category) and 1,600 acres in the 500-year floodplain (48.3%) were converted to developed land uses by 2012 (Tables 2 and 3). During the study period, the largest hurricane that struck Lee County was Hurricane Andrew in 1992. This event is incorporated in the model as a dummy for variables.[1]

In order to account for the variation in net returns to land in agricultural use on the parcel-level scale, soil information data were collected from the United States Geological Survey (USGS). Four variables indexing the soil or land quality were selected to approximate land profitability in agricultural uses. Land Capability Class (*LCC*) of the parcel is a summary

[1] Hallstrom et al. (2005) conducted a quasi-random experiment study in the same county and provided strong evidence that hurricane Andrew in 1992 may have reduced the property values by at least 19 percent in the State Housing Finance Agency (SHFA) zone. Although the study did not differentiate the risk levels, it indicated a significant impact of natural hazards on real estate dynamics.

measure of the suitability of the land for agricultural production. In general, *LCC* is classified in seven grades, with higher *LCC* ratings indicating richer soils more suitable for crop production. Farmland Classification index (*FC*) identifies land as prime farmland (1), farmland of statewide importance (2), or farmland of local importance (3). Drainage Class (*DC*) has three categories and identifies the natural drainage conditions of the soil and refers to the frequency and duration of wet periods (higher index value corresponds to wetter conditions).

Table 1.3 Land Conversion by Flood Zone: Lee County, FL, 1974-2012, 1,000 acres.

| | Developed (1,000 acres) | % of total in same Floodplain category | Undeveloped (1,000 acres) | % of total in same Floodplain category |
|---|---|---|---|---|
| OUTSIDE FLOODPLAIN | 20.7 | 53.1% | 18.2 | 46.9% |
| 100-YEAR FLOODPLAIN | 9.9 | 50.1% | 9.8 | 49.9% |
| 500-YEAR FLOODPLAIN | 1.6 | 48.3% | 1.7 | 51.7% |

A number of other important parcel attributes were identified using the GIS data from the Florida Geographic Data Library (*FGDL*). Parcels' development potential is expected to depend on their spatial attributes such as distances to nearest water bodies, beaches, main roads, cities, schools, and hospitals.[1] For example, proximity to water bodies has two potential impacts on property values: positive from the increased amenity value and negative from a higher flood risk. Parcel size might impact development as smaller parcels are more characteristic of residential development prevalent in the area. Table 4 defines the variables used in the empirical model and provides summary statistics. Economic variables like the housing price index, unemployement rate, and interest rate (10-Year Treasury Constant Maturity Rate) were collected from the Federal

[1] In the FGDL GIS dataset, the distance to the city is the variable measuring distance to the center of Fort Myers.

Reserve Economic Database. Those location attributes and economic variables possess the issues of endogeneity and spatial interdependence which are addressed in the empirical section below.

Table 1.4 Variables Definition and Statistics Used in the Analysis

| Variable | | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| FLOOD100 | Parcel in 100-year flood zone | 0.3 | 0.5 | 0 | 1 |
| FLOOD500 | Parcel in 500-year flood zone | 0.1 | 0.3 | 0 | 1 |
| NOFLOOD | Parcel out of flood zone | 0.6 | 0.5 | 0 | 1 |
| LCC | Capability Class: 1-7 (Class 1 has the lowest limitations/ greatest capability, and class 7 has the highest limitations/least capability)) | 2.0 | 1.0 | 1 | 7 |
| DC | Drainage (Higher class with higher drainage conditions) | 2.1 | 0.4 | 1 | 4 |
| FC | Farmland Classification:1-3(lower class is more suited to use as prime farmland) | 2.49 | 0.71 | 1 | 3 |
| ELEVATION | Elevation (meters) | 17.0 | 8.9 | -1.7 | 41.0 |
| DIST_PARK | Distance to the nearest park (1,000 foot) | 2.1 | 1.4 | 0.0 | 14.2 |
| DIST_ROAD | Distance to the nearest road (1,000 foot) | 0.3 | 0.3 | 0.0 | 4.0 |
| DIST_BEACH | Distance to the nearest beach (1,000 foot) | 26.1 | 10.0 | 0.8 | 52.9 |
| DIST_SCHOL | Distance to the nearest school (1,000 foot) | 2.3 | 1.8 | 0.0 | 11.4 |
| DIST_CITY | Distance to the nearest city (1,000 foot) | 5.2 | 2.8 | 0.1 | 18.5 |
| DIST_WATEBY | Distance to the nearest water body (1,000 foot) | 3.1 | 1.8 | 0.0 | 8.6 |
| DIST_HOSP | Distance to the nearest hospital (1,000 foot) | 13.6 | 6.6 | 0.9 | 34.8 |
| DENSITY | Population density (100 per Sq. Miles ) | 1.9 | 1.3 | 0.01 | 7.1 |
| LOTSIZ | Size of parcel (100 Acres) | 0.061 | 0.55 | 0.0 | 37.1 |
| INRATE10 | Interest rate of U.S. Treasury at 10-year | 7.8 | 1.8 | 1.8 | 8.9 |
| HPI | House price index (1980=100) | 172.9 | 64.6 | 71.8 | 383.9 |
| UNEMPRATE | Unemployed rate | 5.3 | 0.6 | 4.0 | 9.3 |

## 5. Empirical Results

### *5.1. Base Interval Censored Model*

The parameters in equation (4) were estimated using data from 1974 to 2012 broken into seven intervals (1974-1988, 1988-1995, 1995-1999, 1999-2004, 2004-2008, 2008-2012, and after 2012). All the parcels in the sample were in agricultural use in 1974. Estimation results from several empirical models are presented in Table 5. Model 1 assumes a parametric baseline hazard distribution (Weibull) but ignores the interval censoring. Model 2 uses a semi-parametric method—the Cox Proportional Hazards model – that has more flexible distributional specification. Models 3-5 show estimates of a more appropriate interval censored model based on equations (6) to (9). Model 6 reports results of a logit model estimating the simple probability of conversion. This estimation only considers conversion within the period of 1974-2012 and includes only time invariant covariates.

The variables of particular importance to this investigation are those associated with the flood risk. As discussed above, the flood risk is expected to delay conversion decisions by lowering the expected returns from developed uses and also by increasing the value of the real option to convert later.

The results in Table 5 show that the 100-year floodplain dummy coefficients are largely negative and significant across all model specifications and imply an average of 10 percent reduction in the land conversion hazard rate relative to parcels that are not in the flood zone (no flood classification). In terms of the notation in Equation 2, this suggests that expected flood related losses are higher in developed (post-conversion) uses which lowers the net returns in those uses, corroborated by previous research (Chen et al., 2005).

Table 1.5 Estimation Results for Agricultural Land Conversion

| | Parametric Hazard | Cox Hazard | Interval Censoring Hazard Model | | | Logit |
|---|---|---|---|---|---|---|
| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) |
| FLOOD100 | -0.0112 | -0.0179 | -0.00805* | -0.0140* | -0.0310*** | 0.0297 |
| | (0.0272) | (0.0296) | (0.00662) | (0.000824) | (0.00103) | (0.0518) |
| FLOOD500 | 0.0880*** | 0.234*** | 0.0314* | 0.0112** | 0.0420*** | 0.0912* |
| | (0.0318) | (0.0388) | (0.00143) | (0.00107) | (0.00134) | (0.0503) |
| YEAR92 | -2.199*** | - | | -0.271*** | -0.274*** | -0.680*** |
| | (0.0197) | | | (0.00145) | (0.00157) | (0.0957) |
| YEARR92*FLOOD100 | | | | | -0.0075*** | |
| | | | | | (0.00115) | |
| YEARR92*FLOOD500 | | | | | 0.0071*** | |
| | | | | | (0.001) | |
| LLC | -0.0436*** | -0.101*** | -0.00621** | -0.00310*** | -0.0031*** | -0.204*** |
| | (0.00911) | (0.0110) | (0.00255) | (0.000311) | (0.000309) | (0.0207) |
| DC | -0.103*** | 0.218*** | -0.0214*** | -0.00511*** | -0.0052*** | -0.365*** |
| | (0.0208) | (0.0232) | (0.00575) | (0.000698) | (0.000685) | (0.0451) |
| FC | -0.0192 | -0.0520* | -0.00844 | -0.00134* | -0.00149* | -0.152*** |
| | (0.0216) | (0.0275) | (0.00583) | (0.000769) | (0.000766) | (0.0497) |
| ELEVATION | 1.619*** | 3.396*** | 0.290*** | 0.0593*** | 0.0557*** | 3.712*** |
| | (0.174) | (0.204) | (0.0462) | (0.00571) | (0.00572) | (0.372) |
| LOTSIZ | -0.371*** | -0.797*** | -0.0317** | -0.00572*** | -0.0056*** | -0.668*** |
| | (0.108) | (0.205) | (0.0160) | (0.00216) | (0.00215) | (0.193) |
| DIST_PARK | 8.271 | 19.69** | 11.40*** | 0.184 | 0.228 | 8.759 |
| | (6.525) | (7.824) | (1.815) | (0.235) | (0.234) | (15.47) |
| DIST_BEACH | -7.284*** | -13.55*** | -2.555*** | -0.0280 | -0.0249 | -2.492 |
| | (1.120) | (1.264) | (0.275) | (0.0364) | (0.0365) | (2.312) |
| DIST_SCHOL | 18.62*** | 46.63*** | 1.271 | 1.255*** | 1.209*** | 90.23*** |
| | (4.919) | (6.391) | (1.369) | (0.184) | (0.183) | (11.89) |
| DIST_CITY | 12.88*** | 27.18*** | 1.750* | 0.896*** | 0.893*** | 65.94*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (3.161) | (4.162) | (0.903) | (0.119) | (0.119) | (7.865) |
| DIST_WATEBY | -3.36*** | -7.33*** | -3.755** | -1.465*** | -1.418*** | -1.89*** |
| | (0.592) | (0.617) | (1.542) | (0.180) | (0.181) | (0.253) |
| DIST_HOSP | 10.31*** | 18.99*** | 0.415 | 0.0851* | 0.0759 | 10.19*** |
| | (1.551) | (1.747) | (0.396) | (0.0516) | (0.0522) | (3.253) |
| DIST_ROAD | -1.30*** | -2.68*** | -15.84** | -7.138*** | -7.108*** | -4.57*** |
| | (0.266) | (0.302) | (6.33) | (0.789) | (0.790) | (0.512) |
| DENSITY | | | | 0.000570*** | 0.000549*** | |
| | | | | (2.84e-05) | (2.87e-05) | |
| INRATE10 | | | | -0.139*** | -0.138*** | |
| | | | | (0.0048) | (0.0048) | |
| HPI | | | | 0.0300*** | 0.0304*** | |
| | | | | (0.007) | (0.007) | |
| UNEMPRATE | | | | -0.0184*** | -0.0185*** | |
| | | | | (0.000390) | (0.000388) | |
| DISTRICT1 | 0.0497* | 0.113*** | 0.0287*** | -0.00404*** | -0.00380*** | 0.301*** |
| | (0.0278) | (0.0364) | (0.00758) | (0.00102) | (0.00101) | (0.0697) |
| DISTRICT2 | -0.0454* | -0.0916*** | 0.0248*** | 0.00132 | 0.00118 | -0.124* |
| | (0.0265) | (0.0337) | (0.00717) | (0.000963) | (0.000957) | (0.0670) |
| DISTRICT3 | -0.0477* | -0.103*** | 0.00873 | 0.00176* | 0.00139 | -0.177*** |
| | (0.0280) | (0.0343) | (0.00742) | (0.000987) | (0.000987) | (0.0679) |
| DISTRICT4 | -0.0107 | -0.0859 | -0.0193 | 0.00211 | 0.00133 | -0.147 |
| | (0.0466) | (0.0543) | (0.0123) | (0.00148) | (0.00149) | (0.0995) |
| CONSTANT | -3.361*** | | 2.542*** | 3.803*** | 3.800*** | -15.08*** |
| | (0.0752) | | (0.0194) | (0.00690) | (0.00695) | (0.540) |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The 500-year floodplain dummy is consistently positive and significant which implies a higher risk (hazard rate) of conversion relative to the parcels with no flood classification. At least two reasons can be suggested as an explanation. First, parcels in the 500-year floodplain are usually located around creeks and lakes/ponds that, as environmental amenities, may contribute to the land value in developed use. The only control available in the dataset is the distance to a water body that only includes distance to a lake but not a creek. The proximity to running water associated with higher floodplain classification may be the reason for the positive coefficient but we cannot account for it with the available data. Second, it is possible that, due to a much smaller flood probability, the expected flood-related losses on a 500-year floodplain are underestimated due to cognitive dissonance when facing small probabilities of significant flood related losses which can be interpreted as psychological propensity to ignore small probabilities even when potential losses are high (Akerlof and Dickens, 1982 ).

As an illustration, Figure 1 shows the hazard and survival functions for the high (Flood100) and low (Flood500) flood risk areas using the parametric model estimates from Table 5. As expected, hazard rates (survival probabilities) exhibit positive duration dependence. This contrasts with the more frequently observed negative duration dependence due to unobserved heterogeneity and implies lack of persistence of land in undeveloped uses (undeveloped parcels are not robust to conversion), which is not unlikely in fast growing areas like the one considered in this study.

Risk perceptions are considered to have a critical impact on land conversion. Several studies support the hypothesis that past experiences (including recent news) influence people’s perceptions of hazard (Raaijmakers et al., 2008;Wagner et al., 2009). In particular, experiences with natural disasters increase perceived risks and may impact actual investment/conversion decisions. Models 5 to 6 incorporate one extreme event, Hurricane Andrew in 1992, as a dummy variable that indicates the time before (0) or after (1) the event (*YEAR92*). The signs of the *YEAR92* are negative, suggesting lower probability of conversion after a strong flood event, which collaborates the hypothesis of risk revision (either Bayesian updating or increased risk aversion). The interaction terms between the floodplain designation and event year (*F100Y92* and *F500Y92*) have mostly negative signs indicating that the flood risk became a stronger deterrent of conversion of floodplain parcels after the interval that contains the 1992 flood.

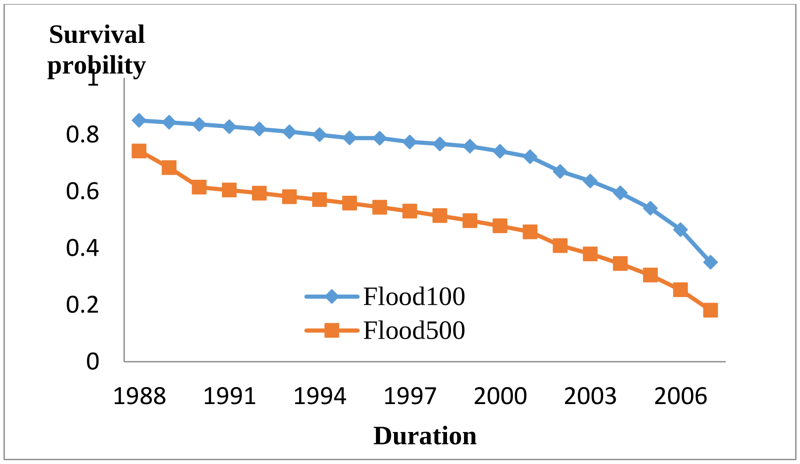


Fig. 1.1 Survival Probabilities in 100 and 500 Year Flood Zones.

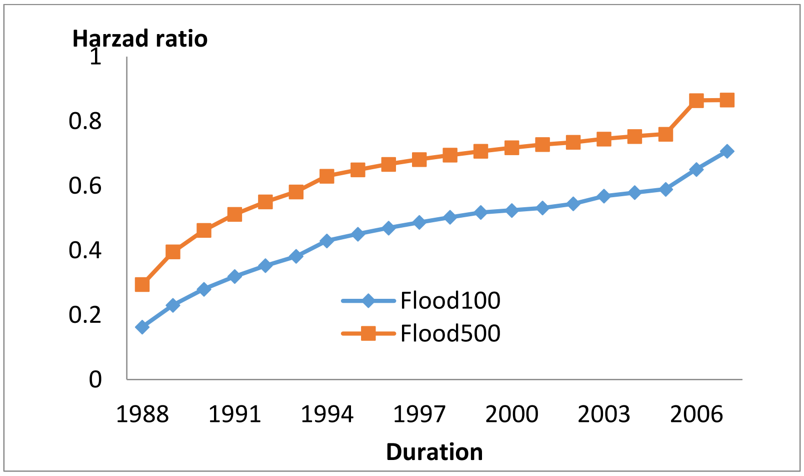


Fig. 1.2 Hazard Ratios in 100 and 500 Year Flood Zones.

Several covariates are used to control for differences in hazard rates across parcels at risk. These variables are expected to affect the relative returns from land, conversion costs, and opportunity costs of conversion. The farmland classification variables (FC) and the soil classification variables (LCC) are significant and negative which is to be expected as parcels with better soils/higher productivity have higher value in agricultural use. Drainage class (DC) is statistically significant and negative implying that better drainage is more important in cropland uses.

Locational attributes also influence the land conversion process: parcels closer to city centers, schools, and beaches, are expected to have higher value in development and are associated with earlier conversion. In particular, increase in the distance to the nearest beach or a water body (lake) reduces the conversion hazard which is consistent with previous studies confirming that the amenity increases the value of the property in a developed use (Batty et al., 2001; Llobera et al., 2003). The distance to a city center is marginally significant, possibly implying that the tradeoff between the desirability of living in urban areas and away from them is leaning towards the latter.

Parcels located near a school have lower conversion hazard, which is counter-intuitive. One possible explanation is a preference for local tax revenue distribution away from the public school needs in more effluent residential communities with higher land values. Distance to main road has a negative and significant impact on the conversion probability and is consistent with results from previous studies (Irwin et al., 2002, 2007). Parcel size is sometimes marginally significant and positive but ambiguous overall, possibly indicating similar economies of scale in both farming and development.

Economic variables are significant determinants of land conversion. Population density has a positive influence on the hazard rate which is plausible since population growth is always considered a major factor affecting conversion of rural parcels (Polyakov et al., 2008). The housing price index (HPI) and long term interest rates affect the conversion hazard rate in opposite directions. House price index is statistically significant and positive, indicating that a unit change in the index is associated with 3% increase in conversion hazard, whereas long term interest rates are significantly negative, suggesting that increasing interest rates decrease the probability of conversion of agricultural lands.

*5.2 Endogeneity and Spatial Interdependence*

Most of the parcel locational attributes (distances to roads, cities, and schools) and some of the economic variables (HPI, unemployment) are likely to be co-determined with the rates of development which makes them endogenous. In order to address the endogeneity issue, we employ a method suggested by Irwin and Geoghegan (2001) that uses a structural economic model. Endogeneity can be explicitly modeled using a system of simultaneous equations (similar to mixed-process models) that includes equations explaining both land use change hazard and potentially endogenous variables (Lillard, 1993). Parameter estimates from the reduced form model are a combination of the parameters from the underlying structural equations (Roodman, 2011). In this exercise, we use the interval censoring hazard model described above.[1] Variables including HPI, distance to city, and distance to road are assumed endogenous (co-determined with conversion). The system of equations is

[1] This was estimated using the user-written CMP routine for STATA that accommodates endogeneity in a system of simultaneous equations (see Roodman, 2011).

$$\begin{bmatrix} h(t) = \alpha HPI + \beta_1 \mathrm{DIST_{ROAD}} + \beta_2 \mathrm{DIST_{CITY}} + \beta X \\ HPI = \gamma_1 h(t) + +\delta_1 \mathrm{DIST_{ROAD}} + \delta_2 \mathrm{DIST_{CITY}} + \delta X \\ \mathrm{DIST_{ROAD}} = \gamma_2 h(t) + \theta_1 HPI + \theta_2 \mathrm{DIST_{CITY}} + \theta X \\ \mathrm{DIST_{CITY}} = \gamma_3 h(t) + \mu_1 HPI + \mu_2 \mathrm{DIST_{ROAD}} + \mu X \end{bmatrix}$$

The reduced form parameters in the hazard equation are estimated and shown in Table 6, Model 1, to be compared with the similar Model 6 in Table 5 which disregards endogeneity.

We also accommodate possible spatial interdependence in the land conversion process. With spatial interdependence, an individual's land use decision is influenced by the neighbors' land use decisions which warrants modeling the process as spatially lagged. Spatial regression models include relationships between an observation and its neighboring values (Kelejian and Prucha, 1999). Cliff and Ord (1975) developed statistical models that accommodate forms of cross-unit correlation and cross-unit interactions. Kelejian and Prucha (2010) used this method to handle other spatial interactions both in geographic and social spaces. Following Kelejian and Prucha (2010), one can expand equation (3) to include the two kinds of spatial dependence by adding a spatially lagged dependent term and a spatial autoregressive error term.

(3b) $h(t) = \rho W h(t) + \beta_0 \lambda_0(t) \phi(\mathrm{X}, \beta) \ + \epsilon, \epsilon = \lambda \mathrm{W} \varepsilon + \mu, \mu \sim \mathrm{i.i.d}$

where $W$ is a inverse distance spatial weight matrix (row-standardized); $\rho$ and λ are the spatial autoregressive coefficients; and μ is a vector of i.i.d. errors with variance σ. The row-standardized spatial weights matrix is calculated based on the parcels' spatial location where the weights are standardized by row. Model 2 in Table 6 shows spatial regressions estimates.

Table 1.6 Estimation Results for Agricultural Land Conversion Hazard with Endogeneity and Spatial Interdependence

| | Structural economic Model | Spatial Model |
|---|---|---|
| | Model (1) | Model (2) |
| FLOOD100 | -0.0393*** | -0.0136* |
| | (0.00980) | (0.004) |
| FLOOD500 | 0.0212** | 0.0111* |
| | (0.00887) | (0.002) |
| YEAR92 | -0.296*** | -1.305*** |
| | (0.000965) | (0.0178) |
| YEARR92*FLOOD100 | 0.000133 | -0.0600*** |
| | (0.000998) | (0.0119) |
| YEARR92*FLOOD500 | 0.0104*** | 0.173*** |
| | (0.00147) | (0.0214) |
| LLC | -0.00228*** | -0.0155*** |
| | (0.000447) | (0.00351) |
| DC | -1.87e-05 | -0.00491 |
| | (0.000884) | (0.00616) |
| FC | -0.00284*** | -0.0250*** |
| | (0.000974) | (0.00694) |
| ELEVATION | 0.00472 | 0.0740 |
| | (0.00709) | (0.0542) |
| LOTSIZ | -0.000494 | -0.0222*** |
| | (0.000589) | (0.00734) |
| DIST_PARK | 0.224 | 4.097* |
| | (0.306) | (2.133) |
| DIST_BEACH | -0.0172 | -1.710*** |
| | (0.0412) | (0.349) |
| DIST_SCHOL | 0.287 | 1.478 |
| | (0.238) | (1.641) |
| DIST_CITY | 0.365** | 1.543 |
| | (0.163) | (1.053) |
| DIST_WATEBY | -1.002*** | -6.805*** |
| | (0.196) | (1.688) |
| DIST_HOSP | -0.388*** | -3.404*** |
| | (0.0598) | (0.512) |
| DIST_ROAD | -2.615*** | -20.08** |
| | (0.847) | (8.045) |
| DENSITY | 0.000212*** | 0.00131*** |
| | (3.36e-05) | (0.000266) |
| INRATE10 | -0.122*** | -3.285*** |
| | (0.000406) | (0.00687) |
| HPI | 0.000556*** | 0.0132*** |
| | (6.72e-06) | (0.000103) |
| UNEMPRATE | -0.0119*** | -0.0150*** |
| | (0.000386) | (0.00482) |

| | | |
|---|---|---|
| DISTRICT1 | -0.00345** | -0.0250*** |
| | (0.00135) | (0.00953) |
| DISTRICT2 | -0.00304** | -0.0468*** |
| | (0.00124) | (0.00878) |
| DISTRICT3 | -0.00603*** | -0.0746*** |
| | (0.00123) | (0.00907) |
| DISTRICT4 | 0.000287 | -0.0224 |
| | (0.00174) | (0.0141) |
| lambda | | 0.0154*** |
| | | (0.00174) |
| rho | | -0.0728 |
| | | (0.683) |
| Constant | 3.798*** | 39.10*** |
| | (0.00700) | (0.0923) |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The reduced form parameters estimated by the system of simultaneous equations (Model 1) are of similar signs compared to the simpler Model 6 in Table 5 but smaller in magnitude. Higher flood risk (FLOOD100) is still associated with a lower probability of conversion to developed uses, while a lower flood risk (FLOOD500) is associated with a slightly higher risk of conversion. The relatively smaller magnitude of the coefficients (~50% of the previous estimates) suggests unobserved drivers of land conversion that are accounted for in Model 1 (Table 6) and lead to over-estimation of the observed variables in Table 5. In the spatial regression (Model 2, Table 6), the spatial parameter lambda is positive and significant suggesting some contagion dynamics in land conversion. This can be interpreted as evidence of urban sprawl as opposed to leapfrogging, the latter resulting from lack of coordination among local governments (Irwin et al., 2001, 2007) and high appreciation of amenities such as open spaces.

Table 1.7 Simultaneous Estimation Results for Land Conversion for Different Types of Rural Land

| | (1)<br>Agricultural land | (2)<br>Rangeland | (3)<br>Forest Land |
|---|---|---|---|
| FLOOD100 | -0.00457** | 0.0240*** | -0.000974 |
| | (0.00190) | (0.00589) | (0.00107) |
| FLOOD500 | 0.00548** | 0.0142** | -0.00354** |
| | (0.00248) | (0.00665) | (0.00172) |
| YEAR92 | -0.571*** | -0.108*** | -0.665*** |
| | (0.00173) | (0.00539) | (0.000902) |
| LLC | -0.00571*** | -0.00472* | -0.00126*** |
| | (0.000805) | (0.00252) | (0.000419) |
| DC | -0.00778*** | -0.000583 | 0.00198*** |
| | (0.00177) | (0.00343) | (0.000763) |
| FC | -0.00465*** | -0.0251*** | 0.00451*** |
| | (0.00168) | (0.00565) | (0.000490) |
| ELEVATION | -0.000434 | 0.0116*** | -0.00356*** |
| | (0.00169) | (0.00407) | (0.000737) |
| LOTSIZ | -0.0407*** | 0.0389 | -0.0123* |
| | (0.0130) | (0.0367) | (0.00645) |
| DIS_PARK | 1.805*** | 5.271*** | 1.490*** |
| | (0.572) | (1.317) | (0.223) |
| DIST_BEACH | -0.215*** | -0.911*** | -0.396*** |
| | (0.0816) | (0.237) | (0.0440) |
| DIST_SCHOL | 1.096** | 5.386*** | 1.055*** |
| | (0.447) | (1.009) | (0.204) |
| DIST _CITY | 0.302 | 4.469*** | 0.652*** |
| | (0.278) | (0.838) | (0.152) |
| DIST_WATEBY | -2.665*** | 4.670*** | 2.221*** |
| | (0.411) | (1.194) | (0.173) |
| DIST_HOSP | -0.101 | 2.810*** | 0.0636 |
| | (0.115) | (0.373) | (0.0634) |
| DIST_ROAD | -9.304*** | -66.38*** | -4.557*** |
| | (1.822) | (3.390) | (0.767) |
| DENSITY | 0.0006143** | 0.000520*** | -1.83e-05 |
| | (6.14e-05) | (0.000163) | (4.77e-05) |
| HPI | 0.00213*** | 0.00475*** | 0.00165*** |
| | (1.12e-05) | (3.68e-05) | (5.98e-06) |
| UNEMPRATE | -0.0284*** | -0.0214*** | -0.0310*** |
| | (0.000887) | (0.00246) | (0.000451) |
| DISTRICT1 | -0.0110*** | 0.00292 | 0.00918*** |
| | (0.00223) | (0.00940) | (0.00130) |
| DISTRICT2 | -0.00970*** | 0.00450 | -7.87e-05 |
| | (0.00206) | (0.00936) | (0.00122) |
| DISTRICT3 | -0.0117*** | -0.00418 | 0.000646 |

| | | | |
|---|---|---|---|
| | (0.00223) | (0.0101) | (0.00135) |
| DISTRICT4 | -0.0144*** | -0.0666*** | -0.00999*** |
| | (0.00339) | (0.0120) | (0.00186) |
| Constant | 2.600*** | 2.399*** | 2.472*** |
| | (0.0182) | (0.0345) | (0.00837) |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### *5.3 Land Conversion by Land Use Type*

We are also interested in the impacts of flood risk on other rural land conversion, such as forest land and rangeland which represent a smaller share of the study area. Equations including the three land uses are estimated simultaneously. By using this approach, on the one hand, we can compare development patterns of different initial land uses. On the other hand, this estimation permits us to control the interaction between different land cover types in the neighborhood. Table 7 displays the estimates for cropland, forest land, and rangeland conversion hazards for comparison purposes. Unlike agricultural land, both floodplain classifications (*FLOOD100* and *FLOOD500*) reduce conversion hazard for forestland likely because of the low flood losses in forestry. In addition to that, local governments make preservation efforts exemplified by the Forest Legacy and Forest Stewardship Programs (FLP and FSP) to protect the "working forests" and help private forest landowners develop plans for sustainable management which boosts returns from land in forestry use. Conversion hazard of rangeland that is supposed to have low losses from floods is increasing in flood risk. As the magnitudes of the impacts decrease with the flood risk, the same explanations offered for the positive coefficient at the 500-year floodplain on farmland may apply.

## 6. Discussion and Conclusion

This study explores how natural hazards affect the probability of land use change decisions and the timing of land use in a largely urban coastal area in Southwest Florida (Lee County). We develop a framework of analysis that incorporates the impacts of flood risks on the hazard of land conversion from agricultural to developed uses. The empirical analysis utilizes a spatially and temporally explicit micro-level data and investigates the impact of natural risks on farm land conversion. The advantage of the duration analysis employed in this research is that it produces estimates of hazard rate distributions allowing to predict conversion probability at different parcel ages and utilizes the most information in censored data. By incorporating locational and economic parcel attributes, we test the hypothesis that natural risks affect farm land conversion.

We estimate several models incorporating interval censored data, time varying covariates, endogeneity, and spatial interdependence. The results show consistent estimates across model specifications of the key variables that have significant impacts on land conversion. We find that flood risk slows down farmland conversion in high risk areas but accelerates it in low risk areas while controlling for other variables suggesting that the differential between flood related losses in developed and agricultural uses generally increases with flood risk. Estimates of the economic and demographic variables such as HPI, population density, and the Federal Reserve interest rate all have expected signs and magnitudes. The results also corroborate previous findings that soil quality and location matters in land conversion. Flood risks have similar impacts on forestland conversion but seem to impact rangeland conversion differently. Incorporating endogeneity and spatial dependence produces similar estimates but of smaller magnitude suggesting the impacts of unobserved factors.

These results can be instrumental in policy design by highlighting the sensitivity of the land market to natural hazards. Empirical literature on uncertainty and the probability of investment uses theoretical models relating uncertainty of returns to the cumulative probability of investment and real option value (Sarkar, 2000). Data and methods like the ones used in this analysis can be used to test the link between uncertainty and hazard rate of conversion (Pennings and Altomonte, 2006). Besides, comparison of the subjectively perceived losses from natural hazards revealed through empirical analysis with the actual hazards can indicate the level of subjectivity in real estate markets.

Proximity to roads, schools, and amenities, as well as education, unemployment, and other economic and demographic characteristics represent a bundle of public goods that come with the land. Empirical estimates of the impacts and feedbacks that these attributes have on conversion can be helpful in understanding and improving the sustainability of regional development. Depending on the initial conditions, positive feedbacks can lead to stagnation or over-development of an area regardless of its natural disaster risks (Bai et al, 2011). Knowing the strengths of these feedbacks can be useful in designing long term development policies.

# Chapter 2

## 1. Introduction

Recently, the United States has experienced the highest levels of North Atlantic hurricane activity in the coastal area. Research has indicated that hurricane activity in the Atlantic Ocean has increased significantly since 1995 (Goldenberg et al. 2001). Warming global climate (Emanuel 2005; Elsner and Jagger 2008) and the Atlantic Multidecadal Oscillation (i.e., the natural cycle) (Klotzbach 2006; Landsea 2007) are two critical reasons attributed to these increased hurricane activity. For instance, the strongest storm during the last 100 years, Hurricane Katrina in 2005, hit the South gulf coast of the United States and, and caused widespread devastation along the central gulf coast states of the U.S. in cities such as New Orleans, LA, Mobile, AL, and Gulfport, MS[1]. More than 1800 people lost their lives due to this disaster, and thousands of more were left without homes, jobs, and social security. Approximately 300,000 homes were destroyed or damaged, and the total economic loss estimated from Hurricane Katrina is approximately $125 billion, with $66 billion in insured losses (Senate 2006).

The post-damages result from a hurricane are unusually caused by the consequences of high wind speeds, storm surges, tidal flooding, high-intensity precipitation, and rainfall-induced inland flooding ( Morton 2002; Wilby 2007). In reality, heterogonous damages are widely

[1] Data source: http://www.ncdc.noaa.gov/special-reports/katrina.html

estimated after the events (Baade et al 2007; Zhigang et al 2001). The outcomes are always beyond the theoretical expectations based on those physical filters and damage functions. Research has revealed significant heterogeneity/variance among affected regions, regardless of locational similarities (different damage estimates in geographically similar areas). Recent studies and data have shown that more frequent and more intense hurricanes are only one of the fundamental causes of increased hurricane-related loss (Landsea et al. 1996; Changnon 2003; Easterling et al. 2000; Pielke et al). Instead, analyses show that at least three social factors—inflation, changing population patterns, and demographic trends—largely account for recent increases in hurricane-related damage (Choi and Fisher 2003). Cutter (2003) interpreted that the hazard potential is either moderated or enhanced by a geographic filter, as well as the social fabric of the regions. The social fabric includes community experiences with hazards, and the ability to respond to, cope with, recover from, and adapt to hazards, which in turn are influenced by economic, demographic, and housing characteristics. Social and biophysical factors interact to produce the overall results. Understanding the heterogeneous impacts of natural disasters across communities is critical for evacuation planning, as well as mitigation and recovery from natural disasters.

Indeed, a lot of research has been conducted to estimate the regional social vulnerability utilizing the advances in geographic information technology and modeling (Bendimerad 2001; Watson and Johnson 2004). Also, significant improvements have been made in predicting, tracking, and assessing expected losses from tropical storms (Katz 2002; Khanduri and Morrow 2003; Pistrika and Jonkman 2010). Some research also provided a micro-level assessment of how social vulnerability influences actual damage in the wake of a disaster. But the relationship between vulnerability and disaster impacts are still in ambiguity.

This chapter specifies the natural damages of Hurricane Katrina in the U.S coastal areas and attempted to implicitly distinguish the causal relationship between disaster impacts and vulnerability. The core objective of this chapter is to test the hypothesis that higher social vulnerability is associated with higher damages. Firstly, we measured the regional vulnerability to natural disaster in the Gulf of Mexico, and then a spatial 2SLS model is constructed to assess how the regional social vulnerability contributes to the distribution of the post-impacts across the study areas. Policy implications are suggested based on the scenario's analysis.

## 2. Natural Disaster Impacts and Social Vulnerability

Social scientists have debated over how to define the concept of "natural disasters" for a long time, while no clear consensus has been reached (Turner et al. 2003; Smit and Wandel 2006; O'Brien et al. 2007). Quarantelli (2000) defines "disasters" as occurrences when "the routines of collective social units are seriously disrupted and when unplanned courses of action have to be undertaken to cope with the crisis. Bolin et al. (1998) and Bolin (2007) extend this idea and point out that "…disasters are fundamentally social phenomena; they involve the intersection of the physical process of a hazard agent with the local characteristics of everyday life in a place and larger social and economic forces that structure that realm. On the whole process of a disaster—causes, preparedness, results and response, and reconstruction—the contours of disaster are strongly tied with the social elements, or formally call this condition "social vulnerability to natural disasters" (Smith 2006).

Social vulnerability to natural disasters is defined by Parry et al (2007) as the degree to which these systems are susceptible to, and unable to cope with, adverse impacts. It indicates a region's capacity to respond and recover from a natural hazards, with minimal damage and the exposure of groups or individuals to stress as a result of social and environmental change (Neil Adger 1999; Cutter et al 2003). Ben (2003) concluded it is a bound of characteristics and capacities of person or group to anticipate the impact of a natural hazard. These characteristics, or social attributes, include socioeconomic status, race, class, gender and educational attainment (Donner and Rodríguez 2008). High levels of social vulnerability are always linked to a range of factors that include access and distribution of resources, technology, information, and wealth, as well as risk perceptions, social capital and community structure, and the existing formalized institutional framework which organize warning, planning and other services (Dolan and Walker 2006).

However, scholars do not acknowledge implicit relationship between disaster impacts and social vulnerability. Chaudhuri (2003) makes a suggestion and indicates “disaster impact” is an ex-post measure of a household’s well-being (or lack thereof). Chaudhuri’s opinion reflects a current state of deprivation, of lacking the resources or capabilities to satisfy current needs. Vulnerability, on the other hand, may be broadly construed as an ex-ante measure of well-being, reflecting not so much how well off a house-hold currently is, but what its future prospects are (Cutter 2005; Ben2003; McCarthy et al. 2001). This explanation implies the possibility of social vulnerability used to predict the damages from a natural disaster of a given strength. This explanation also provides a route to detect the endogenous relationship between impacts and vulnerability over time.

The notion of social vulnerability referring to the influence of social and economic factors/attributes in relation to disasters impacts has been applied in some interdisciplinary studies (Cutter 1996; Oliver-Smith 1996; Oliver-Smith and Hoffman 1999; Cutter and Finch 2008). Classic sociological studies emphasized the pro-social and adaptive dimensions of disaster-related social behavior (Tierney et al. 2006)). For instance, Ryan (2005) focuses on the various ways in which social systems operate to generate ways to cope with disasters. In other words, the actual impacts depend on the characteristics or abilities of a person or a group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard (Ben 2003). Disasters' impacts become a result of social phenomena moderated by the existing social structure. Those socioeconomic characteristics are placed in certain spatial areas and their influence on susceptibility to disasters is tested (Cutter et al. 2003). Existing studies emphasize the impacts resulting from biophysical factors. Pinelli et al. (2004) explains that most studies use post-disaster analysis to develop damage vs. wind speed curves and storm surge. Batts et al. (1980), Georgiou and Davenport (1988), and Vickery et al. (2009) reveal that the distribution of hurricane wind is the critical determinant of damages. Hubbert and Mclnnes (1999), Irish et al. (2008), McInnes et al. (2003), and McInnes et al. (2009) use hurricane-induced surge models to predict disaster loss in the coastal regions. Limited studies use causality tests in damage estimations that include social vulnerability. Bjarnadottir et.al (2011) includes a social vulnerability index in a model for coastal communities at risk of hurricane hazard, ceteris paribus physical factors (e.g. wind speed and surge), to estimate the impacts of climate change.

The following analysis will firstly estimate the Social Vulnerability post-damage after Hurricane Katrina in a census tract level cross the Gulf of Mexico. A structural impact model will be built to estimate how the potential factors contribute to the post-damage following Hurricane Katrina in the Gulf of Mexico. We particularly highlight heterogonous damages from disaster events to the various social characteristics and how the disasters distribute in geographic regions.

## 3. Study Area and Data

Our study area spans across three states (AL, LA, MS) and 13 Counties along the Gulf of Mexico. Unlike most of previous studies, we researched the data at the census tract level. Dependent variable, hurricane impacts (*L*) are estimated by two parts, the one is the immediate damage from the event, and the other is the long-term impacts. The dataset is assembled by the FEMAs' HAZUS which applies standardized methodology that contains models for estimating potential physical, economic, and social impacts of disasters from the hurricane. For Hurricane Katrina, the damages were estimated over a period from August 30 to September 10, 2005. These map layers were made available online through the FEMA's map service and analysis center, and were used to differentiate areas of damage (FEMA 2006).

Hazardous physical factors mainly include two components: wind hazard measured by the H*wind index and storm surge inundation data collected from NOAA (National Oceanic and Atmospheric Administration).  ESRI Shapefile format records a maximum sustained wind speed for each study area according to the distribution of real-time hurricane wind analysis system. FEMA provides three indices (Surge Inundation Limits, Surge Elevation Contours, and High Water Marks) with ESRI Shapefile to measure the storm surge inundation in study area.

The social vulnerability index is constructed from demographic, social, and economic dataset that are drawn from a variety of sources: the U.S. Census Bureau, including the Population Estimates Program; American Housing Survey, 2000 and 2010 Census, Economic Census, and the American Community Survey.  The Hazards and Vulnerability Research Institute (HVRI) at the University of South Carolina has devised a systematical estimation of social vulnerability on the U.S in 2000. However, they do not provide results at the tract level. In this chapter, we strictly follow the HVRI's method to estimate the census tract level's social vulnerability index in study areas.

## 4. Social Vulnerability and Post-impact in the Gulf of Mexico

### *4.1 Census Tract Level Social Vulnerability in the Gulf of Mexico*

SOVI is related to relied socioeconomic, demographic, and built environment variables which the research literature agreed contribute to a community's vulnerability. Following the HVRI's method, five composite factors (14 elements) were collected that differentiate among the coastal communities according to their relative level of social vulnerability. Considering the social and hazard measures have different units, to make it comparable, they were scaled to dimensionless values by the method specified in Davidson and Lambert (2001). This scaling method was chosen because it is not sample specific and, therefore, is easily interpretable. The index using scaling range from 0 to 10, a lower value represents lower vulnerability to the environmental hazards.

(1) $$V_i(t) = \sum_{j=1}^{N}\left(\frac{X_j - X_{j,min}}{X_{j,\max} - X_{j,min}}\right)$$

Where $X_j$ refers to the factor $j$ in the SOVI. The selection of $X_j$ are follows the instruction of Hazards and Vulnerability Research Institute (HVRI) [1].The Social Vulnerability Index is a comparative metric that facilitates inter-census tract comparisons.

Fig. 2.1 represents the spatial distribution of social vulnerability as defined by the SOVI constructed. As expected, the vast majority of census tracts exhibit moderate levels of social

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[1] http://webra.cas.sc.edu/hvri/products/sovi_details_2006.aspx. Instructions on how to calculate this version of SOVI can be found at http://webra.cas.sc.edu/hvri/docs/sovi_32_recipe.pdf.

vulnerability, ranging from 2.8 to 4.3. Most vulnerable census tracts appear in the southern gulf of the Luciana and Alabama-- regions with greater/rapid population growth, as well as with ethnic and racial issues. Vulnerable tracts in Mississippi are distributed in the areas close to the Gulf, where the SOVI index ranges from 4.3-6.8.

### *4.2 Post-damage in the Gulf of Mexico after Hurricane Katrina*

The widespread damage caused by Hurricane Katrina exposed the vulnerability of the gulf coastal counties in vivid detail, where the impact of the event on any given region was not random, but manifested in everyday patterns of social interaction and organization.

The total of residential damages during the event were found using the FEMA's HUZAUS damage assessment polygons, a standardized methodology that contains models for estimating potential economic losses from natural hazards. FEMA has developed a hurricane damage category (FEMA 2006) where:1) limited damage is generally superficial damage to solid structures; 2) moderate damage is when solid structures sustain some exterior damage e.g., missing roof segments, and some mobile homes and light structures are destroyed; 3) extensive damage occurs when some solid structures are destroyed, most sustain exterior damage e.g., roofs are missing and interior walls are exposed, and most mobile homes and light structures are destroyed; and 4) catastrophic damage occurs when most solid and all light or mobile structures are fully destroyed (Table 2.1).

Results indicate 15% of the census tracts are located in the extensive damage and catastrophic damage category. They are mainly located on the west coast of New Orleans and Baton Rouge. An estimated 40,000 population in the whole study area associated high social vulnerability that experienced catastrophic damage and 9,700 persons lived in areas that incurred extensive damage (Gabe et al. 2005). Particularly, in Louisiana, an estimated 2,400 people are likely to have experienced catastrophic damage. Over 60% of this group (or 1,500 people) lived in the Plaquemines Parish, where Katrina first made landfall, which comprises 5% of the parish population (Gabe et al. 2005). Damages in the coastal areas of Mississippi and Alabama are moderate.

When the social vulnerability scores are compared to the hurricane damage estimates in Fig. 2.2, a pattern of differential post-impact and social vulnerability becomes clear. Most of the catastrophic damage and extensive damage areas are associated with higher vulnerability scores. Few areas that sustained the highest levels of damage to their residential structures fall within an area of low social vulnerability (Table 2.2).

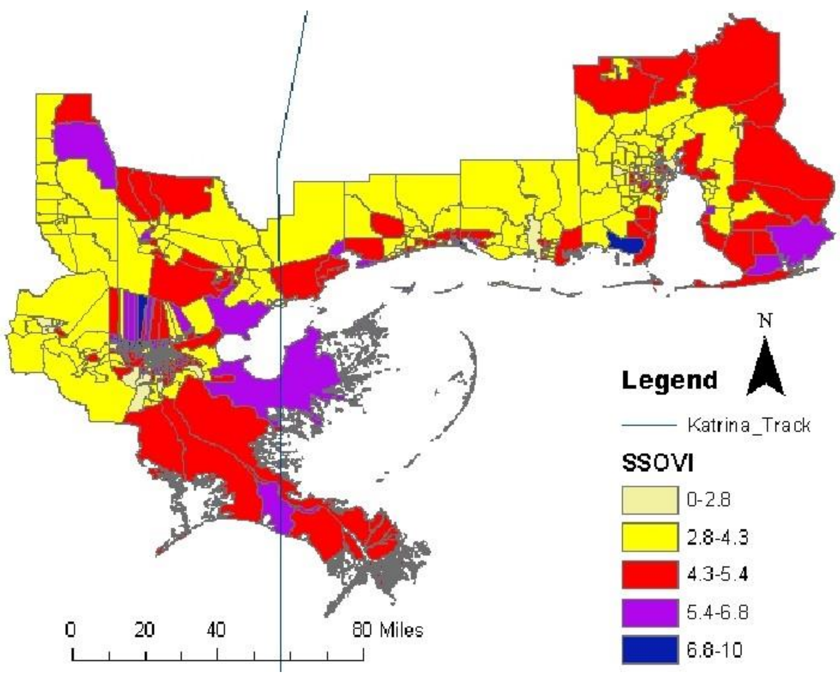



Figure 2.1 Distribution of SOVI in the Study Area

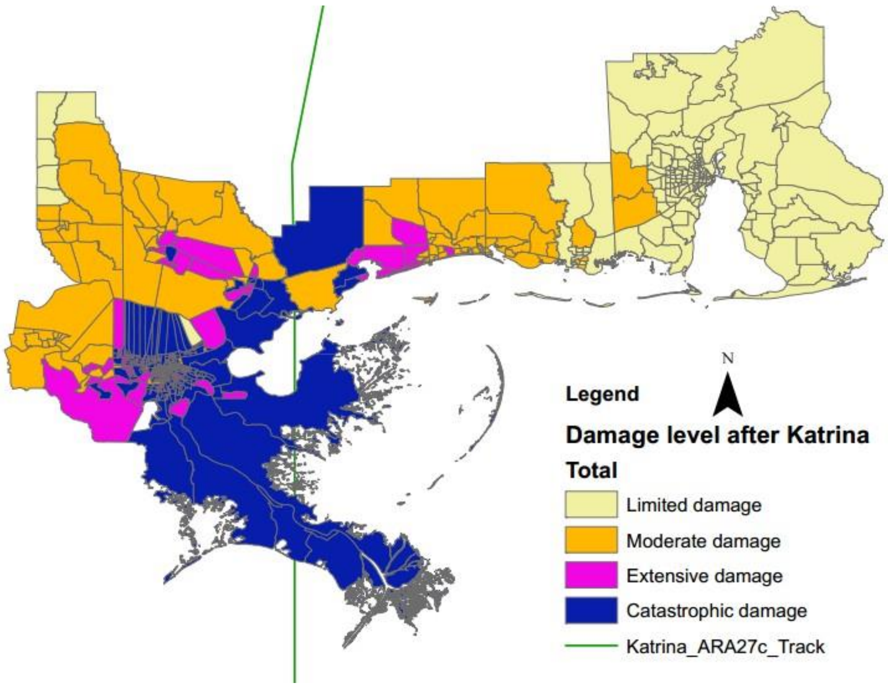



Figure 2.2 Distribution of Total Damage of Hurricane Katrina in the Study Area, 2005

Table 2.1 Summary of Hurricane Kathrine Damages and Geographic Characteristics in overall Sample and Sub-Sample

| Variable | Description | Full samples | | Higher income | | Medina income | | Lower income | |
|---|---|---|---|---|---|---|---|---|---|
| Observation | | 618 | | 84 | | 437 | | 97 | |
| | | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| TOTAL_D | Total damage in the Hurricane (1000$) | 33780.3 | 38362.9 | 23146.2 | 35816.3 | 32323.5 | 35227.8 | 53638.9 | 48940.7 |
| BUILDING_D | Building damage in the Hurricane (1000$) | 20192.1 | 22227.1 | 12899.1 | 17036.7 | 19355.1 | 20640.8 | 32968.4 | 29459.1 |
| CONTENT_D | Content damage in the Hurricane (1000$) | 7886.8 | 9517.3 | 5352.7 | 9731.9 | 7479.0 | 8562.2 | 12935.1 | 12022.0 |
| RELOCAT_C | Relocation cost after the Hurricane (1000$) | 3115.6 | 3461.4 | 2237.3 | 3252.7 | 3036.1 | 3299.6 | 4543.4 | 4079.1 |
| RES | Dollar exposure in residential (1000$) | 156478.9 | 118796.6 | 47642.6 | 29142.9 | 155063.5 | 102016.5 | 289522.5 | 132247.8 |
| COM | Dollar exposure in commercial building (1000$) | 6282.6 | 8974.6 | 4393.0 | 7999.6 | 6752.8 | 9473.7 | 6018.4 | 6917.8 |
| IND | Dollar exposure in industrial building (1000$) | 2177.1 | 5341.1 | 2542.5 | 5864.3 | 2170.8 | 5402.8 | 1788.0 | 4317.1 |
| AGR | Dollar exposure in agricultural building (1000$) | 1617.8 | 26674.9 | 149.9 | 389.2 | 2141.5 | 31714.9 | 588.0 | 787.5 |
| GOV | Dollar exposure in governmental building (1000$) | 1172.7 | 4423.2 | 2131.4 | 8984.1 | 1058.9 | 2874.1 | 657.5 | 2697.4 |
| EDU | Dollar exposure in educational building (1000$) | 1982.9 | 2772.5 | 1591.7 | 2419.6 | 2088.0 | 2941.5 | 1888.0 | 2161.8 |
| HWIND | H*wind speed in Hurricane (mph) | 29.7 | 5.0 | 29.5 | 5.0 | 29.6 | 5.2 | 30.1 | 4.5 |
| SURGE | Highest surge in the hurricane (feet) | 3.9 | 7.2 | 2.0 | 3.9 | 4.5 | 7.9 | 3.2 | 6.2 |
| KATRIAN | Dummy variable if the tract located in the Katrina track | 0.6 | 0.5 | 0.7 | 0.5 | 0.6 | 0.5 | 0.6 | 0.5 |
| DIS_MCITY | Distance to the major cites | 20.2 | 21.7 | 21.7 | 13.8 | 19.8 | 23.4 | 20.1 | 20.5 |
| DIS_ARIPORT | Distance to the major airport | 79.1 | 58.6 | 81.1 | 32.4 | 80.0 | 66.0 | 72.0 | 36.9 |
| DIS_WATER | Distance to water body | 3.4 | 5.6 | 7.7 | 7.4 | 2.8 | 4.9 | 1.6 | 4.2 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| DIS_HWYUS | Distance to major highways | 0.6 | 2.5 | 0.3 | 1.2 | 0.4 | 1.9 | 1.8 | 4.8 |
| DIS_PORT | Distance to major airport | 39.2 | 65.1 | 22.5 | 56.6 | 43.3 | 69.3 | 37.2 | 46.5 |
| ELAVATION | Median Elevation of the tract | 7.6 | 13.9 | 3.8 | 9.4 | 8.5 | 14.7 | 7.5 | 13.8 |
| LA | Dummy variable if the tract located in LA | 0.7 | 0.5 | 0.7 | 0.5 | 0.6 | 0.5 | 0.8 | 0.4 |
| MS | Dummy variable if the tract located in MS | 0.1 | 0.3 | 0.0 | 0.1 | 0.2 | 0.4 | 0.1 | 0.2 |
| AL | Dummy variable if the tract located in AL | 0.2 | 0.4 | 0.3 | 0.5 | 0.2 | 0.4 | 0.2 | 0.4 |

Table 2.2 Summary of SoVI index and Components in overall Sample and Sub-Sample

| Variable | Description | Full samples | | Higher income | | Medina income | | Lower income | |
|---|---|---|---|---|---|---|---|---|---|
| Observation | | 618 | | 84 | | 437 | | 97 | |
| | | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| SSOVI | Social Vulnerability Index | 4.7 | 1.4 | 4.1 | 1.7 | 4.8 | 1.3 | 4.6 | 1.2 |
| QWD9LES | Percent with less than 9th grade education | 5.9% | 3.7% | 8.6% | 3.7% | 5.9% | 3.1% | 2.7% | 3.8% |
| QPOVTY | Percent poverty (median household income less than 15,000) | 21.3% | 8.3% | 31.6% | 7.3% | 21.2% | 6.1% | 10.1% | 3.1% |
| QRENTS | Percent rents | 16.2% | 11.5% | 25.3% | 10.5% | 15.8% | 10.8% | 7.9% | 8.6% |
| QMIGRA | Percent of foreign born | 3.8% | 4.3% | 2.1% | 4.6% | 4.1% | 4.3% | 4.6% | 2.7% |
| QCVLBR | Percent civil labor | 54.2% | 10.9% | 38.1% | 8.9% | 56.2% | 7.8% | 62.3% | 8.6% |
| QAGRI | Percent employment in extractive industries | 0.9% | 1.3% | 0.2% | 0.4% | 0.9% | 1.4% | 1.1% | 0.9% |
| QHEALRY | Percent employment in healthy industries | 6.6% | 2.3% | 6.1% | 2.5% | 6.5% | 2.2% | 8.2% | 2.1% |
| QRICE | Percent rich (median household income greater than $200,000) | 0.8% | 1.5% | 0.2% | 0.3% | 0.6% | 0.9% | 2.3% | 2.9% |
| QHVH | Percent house value higher than $400,000 | 1.4% | 4.0% | 0.2% | 0.5% | 0.9% | 2.0% | 5.0% | 9.1% |
| QASIAN | Percent of Asian | 1.7% | 3.4% | 0.8% | 2.3% | 1.9% | 3.8% | 2.1% | 1.8% |
| QBLACK | Percent of Black | 37.6% | 34.6% | 85.9% | 19.4% | 32.7% | 29.6% | 7.5% | 9.3% |
| QAMERE | Percent of American | 0.4% | 0.8% | 0.2% | 0.2% | 0.5% | 0.9% | 0.3% | 0.3% |
| QHISPAN | Percent of Hispanic | 3.3% | 3.3% | 1.6% | 1.6% | 3.6% | 3.7% | 3.3% | 1.8% |
| QFEMALE | Percent of female | 51.9% | 4.4% | 53.5% | 7.6% | 51.7% | 2.9% | 51.2% | 5.2% |
| QHURRUAL | Percent household in the rural area | 0.17% | 0.65% | 0.02% | 0.17% | 0.23% | 0.75% | 0.06% | 0.31% |
| MCRENT | Mean rent | 413.1 | 136.4 | 274.1 | 88.9 | 412.3 | 100.3 | 577.4 | 162.6 |
| MEDAGE | Median age | 33.7 | 5.8 | 28.4 | 7.5 | 33.9 | 4.6 | 38.5 | 4.8 |
| PPUNIT | People per unit | 2.3 | 0.4 | 2.2 | 0.4 | 2.3 | 0.4 | 2.5 | 0.4 |
| HODENT | Household density (Per unit) | 7.0 | 7.7 | 12.8 | 11.6 | 6.2 | 6.5 | 4.4 | 4.1 |
| PMHSEVL | Mean house value per ace | 307.2 | 487.8 | 422.8 | 550.8 | 280.1 | 476.8 | 314.8 | 451.5 |

## 5. Model and Empirical Framework

### *5.1 Model Structure*

The primary object of this chapter is to build a structural impact model in order to estimate how the potential factors contribute to the post-damage after Hurricane Katrina in the Gulf of Mexico. A basic set of components representing hazard, exposure, and social vulnerability are included in most post-impact models (Burton 2010). The hazard component represents the physical event itself where the principal hazards associated with hurricane characteristics, such as highest wind speeds, storm surge, and induced flood. The exposure describes the number of structures, their value, and other important attributes of the built environment, property or resources that may be impacted by the hurricane (Burton 1993; White, Kates, and Burton 2001; Anderson 1995). Social vulnerability reveals region's capacity to respond and recover from a natural hazard.

Luers et al (2003) s' vulnerability function establishes the linkage between a simulated hazard event and physical damages via social vulnerability components. The function interprets the relationship between social vulnerability and the state of the variables of concern relative to a threshold of damage, the sensitivity of the variables to the stressors, and the magnitude and frequency of the stressors to which the system is exposed. But they fail to explicitly distinguish vulnerability and impact, as well as their causal relationship.

Based on previous practices, the hurricane impact functions in this chapter are defined in multi-dimensions. A structural impact modeling is established by employing the models in studies of Luers et al. 2003, Burton 2010, and Bjarnadottir, et al 2011), where

(2) $$L_i(t) = f(H, E, V|t; \varepsilon) = H_i(t)E_i(t)\prod[V_i(t)]\varepsilon_i(t)$$

$L_i(t)$is the impact (damage) from the hazard event in region $i$ at time $t$. This impact is not only the physical damages that occurs in the process of the hurricane, for example the residential damage, people death, ecosystem disruption, but can be consider as long-term impacts from a disasters, for example migration, cost of repairing or rebuilding, and environmental recovery.

$V_i(t)$ represents a Social vulnerability at time *t* which was modeled using the social vulnerability index (SOVI), which we already estimate in equation (1).

$H_i(t)$ represents the hazard physical factor in region $i$ at time $t$. It usually contains two components, the wind hazard and the surge hazard. Each component has its hazard measures. As Bjarnadottir, et al (2011), the wind hazard measure are built in wind intensity at a specific location or exposure determined with the parameters of distributions (usually assume as a Weibull distribution). The National Oceanic and Atmospheric Administration (NOAA) constructs an index called H*Wind to measure the distributed real-time hurricane wind analysis system. Measure in surge hazard is defined as the surge height, which is affected by the continental slope at a particular site. The National Weather Service (2009) estimates that 60% of Hurricane Katrina damage costs can be attributed to hurricane-induced surge in the waterfront area. Areas affected by storm surge inundation were estimated using NOAA's storm surge model, SLOSH (Sea, Lake, and Over-land Surges from Hurricanes) (Jelesnianski, Chen, and Shaffer 1992; Houston et al. 1999) and the comprehensive hazard measure $H_i(t)$ can be modified as:

(3) $H_i(t) = \zeta_1 H_{W,c} + \zeta_2 H_{S,c}$

Where $H_{W,c}$ refers to the wind hazard at time *t* for exposure category c and $X_{W,c}$ refers to the mean maximum wind speed at time *t* for exposure category *c*. $H_{s,c}$ refers to the surge hazard at time *t* for exposure category *c* and $X_{W,c}$ refers to the mean surge height at site at time *t* for exposure category $c$. $\zeta_1$and $\zeta_2$ are constants that can be varied to represent different weightings of $H_{W,c}$ and $H_{S,c}$.

$E_i(t)$ is the function of exposure to the hazard. It is always treated as a function of physical factors in the empirical estimation (Turner et al. 2003). An explicit example of measuring the exposure to the hazard is to use the coefficients $\zeta_1$ and $\zeta_2$ in equation 2, which refer to exposures in a given category. Luers (2003) measures the exposure as an expected value in regions. This measurement defines the exposure as a function of vulnerability.

Substituting equation (1), (3) and (4) into (2), the specific hurricane impact model can be represented as,

(4) $$L_i(t) = (\zeta_1 H_{W,c} + \zeta_2 H_{S,c}) \cdot \left( \sum_{j=1}^{N} s_j \left( \frac{X_j - X_{j,min}}{X_{j,\max} - X_{j,min}} \right) \right) \cdot E_i(X_{ji}) \cdot \varepsilon_i(t)$$

*5.2 Model Specification*

The model emphasizes focus on the regions as well as the factors that contribute to the hurricane post-impact. The analysis uses data from the census tract level relating to the coast of the Gulf of Mexico. Based on the structural model, the estimation specifies the hazard damage as a function of the hazard factor, social vulnerability, and other variables (such as elevation, soil and drainage) that might influence the estimated damage. The basic model with a standard linear formulation is:

(5) $$lnL_i = \beta_0 + \beta_1 WIND_i + \beta_2 SURGE_i + \beta_3 SOVIs_i + \beta_4 DISTANCEs_i + \varepsilon$$

Where $L$ represents the post-damaged level (usually measured as the percentage damage in a given area) in or after the event; $WIND$ are maximum sustained winds; $SURGE$ is average storm surge inundation; and $SOVIs$ is the social vulnerability index measure that incorporates a number of variables. $DISTANCE$ refers to the distance from a given tract to a specific point (e.g. city, transportation etc.).

The analysis for this paper was conducted at the census tract level of geographical data. It is important to consider to what extent changes in spatial scale, aggregation, and interaction, which may have led to different, possibly contradicting final, results (Clark and Avery 1976; Openshaw 1983; Openshaw and Turton 1996). As pointed out by Tobler (1970), "*all places are related but nearby places are more related than distant places*." Schmidtlein et al. (2008), and several other studies indicate that the relationships between variables aggregated to those levels will change as the scales of analysis change. Social and physical phenomena are often highly clustered in space (e.g. regional voting patterns, racial segregation, the poverty belt, housing values, crime, farm crops, etc.), which will largely interact with each other (Poole and Rosenthal 1985; Benford and Fahlén 1993; Wong et al. 2006; Banks, Duggan et al 2006). Spatial regression models include relationships between variables and their neighboring values, and allow us to examine the impact that one observation has on other proximate observations (Kelejian and Prucha 1999; Krugman 1992). Cliff and Ord (1975, 1981) developed statistical models which accommodate forms of cross-unit correlation and cross-unit interactions. Kelejian and Prucha (2010) and Drukker et al. (2010) use this method to handle other spatial interactions both in geographic space and social-interaction. Following Anselin (1988), Arbia (2006), and Haining 1993), one can expand equation (6) to include the two kinds of spatial dependence, thus making explicit the *n* census tracts of our case:

(6) $$lnL_i = \rho W lnL_i + \beta_0 + \beta_1 WIND_i + \beta_2 SURGE_i + \beta_3 SoVIs_i + \beta_4 DISTANCEs_i + \epsilon$$

$$\epsilon = \lambda \mathrm{W}\varepsilon + \mu, \mu \sim \mathrm{i.i.d.}$$

where $W$ is a spatial weight matrix; $\rho$ and λ are the spatial autoregressive coefficients; and μ is a vector of i.i.d. errors with variance σ.

Moreover, as the analysis unfolds, issues of endogeneity will transpire in the variables $SOVIs_i$, because it might have a correlation with the error term. We use an instrumental variables to identify the strength of the association between social vulnerability and damage, by means of the analysis of the causal effect of social vulnerability index on the damage. Following most of studies, we choose the regions dummy variables as the instrument variables used in a two stage estimation. An advantage is it included all the unobserved factors in each region.

## 6. Results

### *6.1 Econometric Results of social vulnerability to post-damage*

To test the assumption that the social vulnerability contributes to the hurricane damage prediction, a multivariate regression model was chosen after satisfying regression's general assumptions. We began with the OLS regression. The OLS residuals were used to test for possible spatial dependence, and to provide guidance on how to proceed towards the final model specification. To make the impact of hurricanes in the regions in the same scale, we use the percentage damage (estimate damage over total value of property) as the dependent variable. Social vulnerability is measured by a number of social and demographic characteristics first in Table 2.3, and then combined by a SOVI index in Table 2.4.

In table 2.3, model 1 included the factors comprised the SOVI index. Model 2 and model 3 add extra variables, like geographic characteristics, as controls. Results indicate most social factors are significantly associated with the percentage of damage. The spatial dependence parameter estimate ($\rho$) turned out to be positive and significant, which indicates that the effects have spilled over since they are influencing each other's impacts positively.

Table 2.3 Estimate Result of the Social Factors on the Percentage Damage of Hurricane Katrina in the Study Area, 2005

| Dependent variable = Percentage damage in the census tract | | | |
|---|---|---|---|
| VARIABLES | (1) | (2) | (3) |
| QWD9LES | -8.501 | -0.0962 | -6.090 |
| | (15.26) | (14.17) | (13.82) |
| QPOVTY | 37.01*** | 36.11*** | 40.82*** |
| | (10.23) | (9.409) | (9.113) |
| QRENTS | 43.20*** | 48.28*** | 50.23*** |
| | (7.672) | (7.248) | (7.128) |
| MEDAGE | -0.00630 | -0.155 | -0.129 |
| | (0.114) | (0.109) | (0.105) |
| HODENT | 0.315*** | 0.291*** | 0.336*** |
| | (0.0848) | (0.0858) | (0.0855) |
| QMIGRA | 67.22*** | 45.75*** | 44.35*** |
| | (18.96) | (17.30) | (16.67) |
| QCVLBR | -2.685 | -8.445 | -9.947* |
| | (5.809) | (5.491) | (5.359) |
| QAGRI | 294.0*** | 294.9*** | 188.4*** |
| | (38.09) | (36.27) | (41.16) |
| QHEALRY | -40.29* | -26.89 | -23.07 |
| | (20.92) | (19.26) | (18.66) |
| PMHSEVL | -0.000699 | -0.00170 | -0.00192 |
| | (0.00124) | (0.00127) | (0.00123) |
| QRICE | 9.800 | 22.02 | 27.33 |
| | (29.02) | (26.69) | (26.32) |
| QHVH | 20.61 | 20.04* | 16.17 |
| | (12.80) | (11.78) | (11.41) |
| Z_PPUNIT | 1.746*** | 1.346** | 1.494** |
| | (0.657) | (0.618) | (0.620) |
| QASIAN | -48.10*** | -37.06** | -40.58** |
| | (17.56) | (16.27) | (16.34) |
| QBLACK | -0.747 | -0.820 | -1.047 |
| | (2.131) | (2.169) | (2.183) |
| QAMERE | 53.12 | 51.65 | -6.229 |
| | (49.26) | (45.47) | (46.32) |
| QHISPAN | 19.19 | 9.705 | 17.57 |
| | (19.01) | (18.22) | (17.69) |
| QFEMALE | -36.63*** | -41.27*** | -42.20*** |
| | (10.08) | (9.311) | (9.055) |
| MCRENT | 0.00381 | 0.00446 | 0.00688* |
| | (0.00450) | (0.00415) | (0.00404) |

| | | | |
|---|---|---|---|
| QHURRUAL | 27.59 | -6.759 | 58.31 |
| | (71.10) | (68.85) | (67.35) |
| HWIND | 0.459*** | 0.131 | 0.331** |
| | (0.132) | (0.145) | (0.151) |
| ELE | -0.244*** | -0.0589 | 0.0260 |
| | (0.0629) | (0.0667) | (0.0731) |
| KATRIAN | 9.326*** | 6.853*** | 5.395*** |
| | (1.222) | (1.447) | (1.476) |
| ELAVATION | -0.0894** | -0.0881** | -0.0748 |
| | (0.0386) | (0.0427) | (0.0485) |
| DIS_SHOPCENT | | | 26.13*** |
| | | | (8.959) |
| DIS_MCITY | | | 40.08* |
| | | | (23.82) |
| DIS_ARIPORT | | | 10.21 |
| | | | (9.340) |
| DIS_WATER | | | -148.9* |
| | | | (90.10) |
| DIS_HWYUS | | | -31.13 |
| | | | (140.1) |
| DIS_PORT | | | -18.91** |
| | | | (7.788) |
| D_URBAN | | | -1.037 |
| | | | (2.711) |
| LA | | | 1.615 |
| | | | (2.181) |
| MS | | | -7.955*** |
| | | | (2.273) |
| SUGERCOSTAL | | | 0.105 |
| | | | (0.0929) |
| lambda | | 0.236* | 0.0459 |
| | | (0.121) | (0.131) |
| rho | | 4.006*** | 3.950*** |
| | | (0.0716) | (0.161) |
| sigma2 | | 66.23*** | 61.05*** |
| | | (3.806) | (3.510) |
| Constant | -3.158 | 16.51* | 11.11 |
| | (9.083) | (8.662) | (8.887) |
| Observations | 606 | 606 | 606 |
| R-squared | 0.686 | | |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4 indicates the results when we use a SOVI index instead of the social factors. Endogeneity issues are addressed by a spatial two stage lest square estimation. We select a region's dummy variables' as instrument variables, which obviously strongly relate to the social vulnerability, but are weakly associated with the estimated damage. The standardized parameter estimates in Table 2.4 relats the Katrina's post-impact to both the modeled physical and social parameters for different levels of damages. As expected, results suggest that the social vulnerability contributes significantly to the total damages within the study areas. Conventionally, regions with relatively higher social vulnerability are associated with higher levels of disaster damage. This result is consistent with the finding from Masozera, Bailey, and Kerchner (2007), Zahran et al. (2008), and Burton (2010), although they didn't provide a econometrical estimation of the relationship between disaster damage and social vulnerability. Center (2000) also found that social vulnerability tends to increase the impact potential, especially as more people and property are aggregated. The socially vulnerable or disadvantaged households, on one hand, have lower levels of disaster preparedness (Mileti and Darlington 1997; Russell, Goltz, and Bourque 1995; Peacock, Brody, and Highfield 2005; Miceli, Sotgiu, and Settanni 2008); on other hand, socially vulnerable groups are less likely to receive and believe official disaster warnings. This might make them underestimate the coming disasters (Fothergill and Peek 2004; Perry and Lindell 2008; Lindell and Perry 2012). Besides, higher social vulnerability regions are always associated with lower income and education, higher poverty ratio, population density and median age, as well as higher proportion of females and African American households. Those characters might lead to socially vulnerable populations suffering disproportionately in terms of property damage, injury, and death, which have been proven by the estimated results in Model 2 and Model 3. When include all these social-economic variables in the model are assessed, most of them show a significant contribution to the damage after Hurricane Katrina. Norris et al. (1999) and Peacock, Brody, and Highfield (2005) have found that both low income and African American households are less likely to have adequate shuttering to protect their homes from hurricane damage. Wright (1979) and Lindell and Prater 2003) find that lower income households experience significantly higher rates of injury, and property loss with regard to the hurricane. Fothergill and Peek (2004) note that nearly 40 percent of all tornado fatalities occur in mobile-home parks, which are significantly more likely to house persons of lower income.

Table 2.4 Estimate Result of the SSOVI Index on the Percentage Damage of Hurricane Katrina in the Study Area, 2005

| Dependent variable = Percentage damage in the tract. | | | |
|---|---|---|---|
| VARIABLES | (1)2SLS Spatial OLS | (2) 2SLS Spatial OLS | (3) 2SLS Spatial OLS |
| SSOVI | 1.365*** | 1.160*** | 1.091*** |
| | (0.358) | (0.355) | (0.369) |
| HWIND | 0.316* | 0.407** | 0.397** |
| | (0.167) | (0.168) | (0.182) |
| ELE | -0.0574 | -0.178** | -0.142 |
| | (0.0863) | (0.0887) | (0.0914) |
| KATRIAN | 6.500*** | 4.712*** | 4.690*** |
| | (1.653) | (1.645) | (1.767) |
| ELAVATION | -0.0670 | 0.0219 | 0.0223 |
| | (0.0430) | (0.0549) | (0.0576) |
| COSTAL | | 6.202*** | 10.35*** |
| | | (1.788) | (3.185) |
| DIS_SHOPCENT | | 25.20*** | 25.53** |
| | | (9.742) | (10.15) |
| DIS_MCITY | | 17.09 | 17.95 |
| | | (22.52) | (25.14) |
| DIS_ARIPORT | | 14.50 | 13.33 |
| | | (10.42) | (11.11) |
| DIS_WATER | | -66.46 | -68.52 |
| | | (91.89) | (102.0) |
| DIS_HWYUS | | -132.3 | -133.9 |
| | | (173.7) | (177.0) |
| DIS_PORT | | -25.18*** | -23.46** |
| | | (9.052) | (9.358) |
| D_URBAN | | 1.844 | 1.737 |

| | | | |
|---|---|---|---|
| | | (3.440) | (3.442) |
| LA | 4.401** | 6.024*** | 6.489*** |
| | (1.808) | (1.931) | (2.309) |
| MS | -0.611 | 0.152 | 1.122 |
| | (2.287) | (2.273) | (2.613) |
| SUGER*COSTAL | | | -0.312 |
| | | | (0.202) |
| Constant | -11.27** | -18.17*** | -18.33*** |
| | (4.643) | (5.968) | (6.409) |
| lambda | 0.526*** | 0.636*** | 0.665*** |
| | (0.163) | (0.152) | (0.117) |
| Rho | 0.988*** | 1.010*** | 2.722*** |
| | (0.302) | (0.274) | (0.774) |
| sigma2 | 113.3*** | 104.8*** | |
| | (6.516) | (6.025) | |
| Observations | 606 | 606 | 606 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As observed, regional impacts are more frequently affected by the storm wind speeds, where the parameter contributes significantly to the damage on the census tract level. At the time of Hurricane Katrina's landfall, aircraft data measured from dropwindsondes indicates a high-end Category 3 hurricane. The strongest surface wind measured by dropwindsonde occurrs in the storm's right-front quadrant, where two sondes estimate winds at 99 kilometers (Knabb, Rhome, and Brown 2005). Although the storm surge inundation generates negligible direction for the the coefficient, the positive parameter in the interaction partition between surge inundations and coastal also suggests that hurricane damages are significantly influenced by storm surge inundations in given wind speed. What's more, the census tracts in the path of Hurricane Katrina obviously suffered severe damage. This finding is contrary from some of research which mentioned the 'impact waive' of the 'Hurricane's eye' along the hurricane path (Burton 2009). Relatively lower loss might occur in the Hurricane's eye regions, because of the weak wind-speeds seen along the Hurricane's eye.

The location characteristics and distance are shown to be of no real importance to the damages. Insignificant elevation parameter suggests the homogeneity characters in geography. The negative signs on the distance to water and port reveal that much of the destruction comes from severe storm surge. Rather than the following flood, the water body provideds a natural buffer against the winds. One might expect tracts close to big cities and urban regions to suffer larger damages since they might expose more values, e.g., properties and population. Surprisingly, these regions seem to have comparatively less damage. In view of the relatively higher level quality of properties, preferable rescue and evacuation, and comprehensive flood control facilities, show benefit to reduce the results of the hazard.

### *6.2 Simulation and sensitivity analysis*

The marginal effect (elasticities) for the social vulnerability and post-damage on selected parameters obtained from impact function estimations are given in Table 2.5. Six important parameters are reported respecting the significant effect on the social vulnerability (SOVI) and post-damage across the hurricane event. In the pooled dataset, most elasticities have the expected markers. For example, education and population density positively influence both on social vulnerability and post-damage, while the effects from improving in healthy sectors indicate a negative sign both on social vulnerability and post-damage. The lagest sensitive effect on SOVI is -8.7, where the marginal effect from percentage employment in healthy sectors to social vulnerability. This means 1% increase in the employment in healthy sectors suggests 8.7% decrease in social vulnerability and associated 0.5% post-damage after Hurricane Katharina. The most sensitive effect on post-damages are 2.4, where the marginal effect from percentage house rent in the census tract, which indicates 1% increase in the employment in healthy sectors, this will aggravate the post-damage by 2.4%.

Table 2.5 Summary of Effects Elasticities on Selected Parameters Obtained From Impact Estimation

| | Pooled Data | | Low income level | | Medium income level | | High income level | |
|---|---|---|---|---|---|---|---|---|
| | SO VI | Dama ge | SO VI | Damage | SO VI | Damage | SO VI | Damage |
| % less than 9th grade education | 3.6 | 0.9 | 5.8 | 4.1 | 3.6 | 3 | 3.9 | 0.7 |
| % house rent | 2.3 | 2.4 | 2.9 | 2.6 | 2.8 | 2 | 1.4 | 2.4 |
| % higher house value | -4.1 | 0.7 | -2.1 | 1.4 | -4.1 | -0.2 | -4.8 | -0.5 |
| Population density | 1.3 | 1.1 | 1.6 | 1.4 | 1.3 | 0.8 | 0.9 | 0.6 |
| % civil labor | 0.8 | -0.9 | 1.4 | -1 | 1.3 | -0.5 | 1.3 | -0.7 |
| % employment in healthy sectors | 8.7 | 0.5 | 8.9 | 0.6 | -8.3 | 0.3 | 8.4 | 1.4 |

More interesting stories are promoted by examining the responses to the disaster in different income groups. The full dataset was divided into three subgroups based on median income. Elastisities are collected by two stage spatial model estimation, shown in Table 2.5. In general, factors are more sensitive to social vulnerability and post-damage in the lower income level group except the factor of percentage higher house. Recent empirical reports by Elliott and Pais (2006) and  Logan (2006) also support that poor may have suffered disproportionately higher levels of damage. Poor people always correspond to poor living conditions with less money to spend on preventative measures, emergency supplies, and recovery efforts (Clark et al. 1998). What's more, poor people are more likely to live in poorly built housing, which can be a major disadvantage when disasters occur (Clark et al. 1998). During disasters, the poor suffer from higher mortality rates (Benjamin Wisner 2004) and greater housing damage (Morrow 1999). Thus, small improvements on house building, community environment, and education will possibly cause a lager response for social vulnerability and post-damage.

The response from percentage higher percentage houses indicates ambiguity results cross the income group. In the lower income group, the elasticity for the social vulnerability is negative with a relative lower value, which is -2.1 compared with -4.8 in the higher level income group. While the elasticity for the post-damage are positive, some are negative in the median and high income level group. This implies the impacts for social vulnerability from increasing percentage of higher value house are more sensitive in higher income level group, but more robust in lower income level groups. The corresponding post-damage is even increased in the poor areas but decreased in the rich areas. Laska and Morrow (2006) indicates that although the absolute monetary value of the economic and material losses of the poor may be less than those of the wealthy, the losses sustained by the poor are far more devastating. The higher quality houses built in the poor communities, although may slightly increase the global social vulnerability in the areas, possibly aggravate the post-damage because of the poor preventative, assistant system, emergency supplies, and recovery efforts in the community. Conversely, people living in relatively wealthy districts have capacity to respond and recover from a natural hazard with minimal damage (Cutter et al. 2003). The wealthy are capable of reaching accommodation to actual or expected climate stresses, or to cope with the consequences (McCarthy et al. 2001), and to effectively respond to a change in climate.

### *6.3 Simulation and policy strategy*

Here we present simulations that show how the six important factors of changing, might affect the relative sensitivity of the social vulnerability and post-damage. Simulation is performed by increasing or reducing the magnitude of factors value by 1% in the measured data set. The conditions of the six simulations are summarized in Table 2.6. The intention of these simulations is not to provide an exhaustive analysis of all possible response patterns. We have chosen them to explore how differences in regions can affect elasticity patterns of social vulnerability and post-damage to potential exposure in realistic political solutions and strategies.

Table 2.6 Summary of Simulated Scenarios.

| Scenario | % less than 9$^{th}$ grade education | % rent | % higher house value | Household density | % civil labor | % employment in healthy sectors |
|---|---|---|---|---|---|---|
| S1 | -1% | None | None | +1% | None | None |
| S2 | None | +1% | +1% | None | None | None |
| S3 | None | None | None | None | +1% | +1% |
| S4 | -1% | +1% | +1% | None | None | None |
| S5 | -1% | +1% | None | None | +1% | +1% |
| S6 | -1% | +1% | +1% | +1% | +1% | +1% |

Table 2.7 shows the changes in social vulnerability and post-damage and their bootstrap-estimated 95% confidence limits for the measured data (control) and for the six simulations. Simulations indicate that almost all the changes respective to the social vulnerability are reduced significantly in all simulated scenarios. Scenario one (S1) indicates the largest reduction in social vulnerability, ranging from 9%-14%, combining the effects from both improving on education (-) and population density (+). The significant effect from education improvement will offset the negative effects from increases in population density. This will reduce the social vulnerability to the natural disaster. But the associated responses on the post-damage are modest. Damage is only reduced in the median and high income level groups, but still increase in the low income level group.  The most sensitive changes in post-damage are suggested in scenario one (S4) with average 3.3% increase, and 4.7% increase in low income level group, and 1.6% reduction in higher income level groups. The impacts from changing in House value and house rent situation are dominant in this scenario. Especially in the low level income group, impacts from these two factors with a positive sign are over the negative effect from education improvement, and make a significant post-damage increase in this group.

Table 2.7 Bootstrap Estimates of 95% Confidence Intervals of Changes in Social Vulnerability and Post-Damage

| | Pooled Data | | Low income level | | Median income level | | High income level | |
|---|---|---|---|---|---|---|---|---|
| | SOVI | Damage | SOVI | Damage | SOVI | Damage | SOVI | Damage |
| S1 | -11.3 | -1.1 | -13.7 | 0.7 | -11.3 | -6.2 | -12.6 | -8.7 |
| S2 | -0.5 | 3.1 | 0.8 | 4 | -1.3 | 1.8 | -3.4 | 1.9 |
| S3 | -8.3 | -1.4 | -7.5 | -1.6 | -7.9 | -0.8 | -7.1 | -2.1 |
| S4 | -4.1 | 3.3 | -3.4 | 4.7 | -3.6 | -0.4 | -6.4 | -1.6 |
| S5 | -9.6 | -1.7 | -10.4 | 0.3 | -8.7 | -1.8 | -9.6 | -3.8 |
| S6 | -12.4 | 1.9 | -10.9 | 3.1 | -11.5 | -1.2 | -13.5 | -3.7 |

This analysis demonstrates the importance of determining the relative sensitivity of social factors to social vulnerability and post-damage in different income level. Our simulations demonstrate how the relative importance of social factors to social vulnerability and post-damage may be highly variable and dependent on additional influences, such as the effects of economic development and technology innovation. Our ability to assume the changes in social vulnerability and post-damage may be provided as a reference for political strategy in realistic scenarios to prevent the natural disasters in the future.

## 7. Discussion and Conclusions

Economic and social changes in the decades constitute an influx of people to the Southeastern United States, although, hurricane frequencies and losses in this area are the greatest (Burton 2010). Hurricanes have increasingly aggravated the damages in the coastal areas. Those losses trigger redistribution on the population flow trends, economic development, and societal vulnerability to the natural disasters. The relevant demographic shifts in coastal metropolises have evacuated the densely populated urban areas after disasters (Schwarz et al 2010; Kaugurs 2011; Wiechmann and Pallagst 2012), while the increasing trends of damage results from natural disasters have never been stopped. It is important to recognize the reasons why certain groups are vulnerable in certain events, and how to improve the response capabilities and preparedness for natural disasters.

The objective of this chapter is to examine the relationship between location-based social vulnerability and post-disaster impacts, including estimated damage, migration, and recovered cost in the U.S. Gulf Coast region following Hurricane Katrina. We use a factor analysis to develop a regional index of social vulnerability, and examine how its various dimensions are related to heterogonous damages from the storm. By employing spatial analysis techniques, we identify significant relationships between the emergent dimensions of social vulnerability and regional losses following Hurricane Katrina. The results reveal a place-based social vulnerabilities index in the Gulf Coast regions. Clear social vulnerabilities distributions are revealed in the shaping of census tract-level. This dovetails with other vulnerability studies attract more attention paid to the social-demographic characters in the pre-disasters ( Bohle et al 1994; Enarson 2002; Gooden et al. 2009 ). In particular, this analysis also measures the vulnerability using the existing data in gulf area, which might aid preparedness for further events.

The factors identified in the econometric analysis are consistent with the broader hazards literatures included in the analysis which demonstrate social vulnerability to the hurricane damage, the causes from geographic variability, and physical hurricane factors. Findings suggest that a significant between social vulnerability and post-disaster damage estimates and highlights the importance of spatial attributes of the affected areas. The vulnerability index is only significant in the low and median income groups while the impacts to the catastrophic disaster of Hurricane Katrina show ambiguity in the higher income regions. These findings are supported by

Guimaraes et al. (1993), Rhodes et al. (2010), and Lowe, et al. (2010), who demonstrate the damage distribution across the income communities.

Predicted results from sensitivity analysis suggest the change of patterns in six important factors related to the social vulnerability and post-damage. Relevant policies are encouraged to modify the relationship among the physical, social, and economic factors. Necessary aids to the victims could be considered as a short run in support of the recovery from disasters, while the critical practices are to improve the capacities to cope with the disasters.

**Chapter 3**

## 1. Introduction

Improving physical and institutional infrastructure, transportation, irrigation, and sewer systems, have been widely used to motivate and sustain long term agricultural development. However, it is not always a priority for policy-makers because such programs require large investments and long gestation periods (Barker and Hayami, 1976). Alternatively, governments, especially in the developing countries, prefer to adopt some temporary policies, such as supporting product price or subsidizing inputs, to stimulate an increase in output along an existing production function. For example, subsidies to the fertilizer industry in China have increased by 670%[6]since 2003. Currently, the government has spent about RMB 20 billion yuans on fertilizer companies, as part of the national policy, to achieve self-sufficiency in food staples and improve the farmers' income. Those subsidies might bring economic benefits to society, but can also be a major cause of negative environmental externalities as it promotes excessive use of fertilizers, agrochemicals and irrigation water.

Agricultural input subsidies have long been used to promote smallholder farmers' use of inputs, increase wages, reduce food prices, and promote economic growth and it is a common element in agricultural development in poor rural economies in the 1960s and 70s, including successful green revolutions (Crawford et al., 2003). Although subsidies have continued, to a

[6]This data come from Cheng (2010)'s report 'The true cost of the N-fertilizer (in Chinese)', which is a program hold by Renmin University of China.

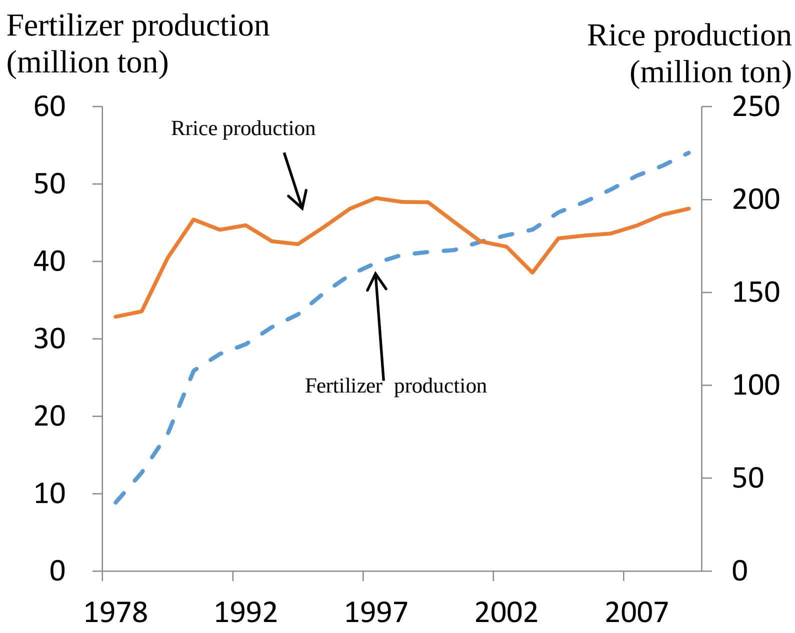
greater and lesser extent, in some countries, conventional wisdom as well as dominant donor thinking in the 1980s and 1990s was that subsidies had been ineffective and inefficient policy instruments in some developing countries , contributing to government overspending and fiscal and macroeconomic problems (Andrew and Chirwab 2011; Xu et al. 2009). Filipski and Taylor (2012) compared the potential effects of three transfer mechanisms on incomes and welfare in rural areas: An input subsidy (IS) and cash transfer (CT) modeled on actual programs in place in Malawi and Ghana; and a farm gate market price support (MPS). Although they concluded income transfers affect both beneficiary and non-beneficiary households in complex ways, they also support that input subsidies easily dominate market price supports as a way of transferring income into the small scaled famers. Under some arguably plausible conditions, both input subsidies and market price supports may be more efficient than cash transfers. Brooks, et al. (2008) indicated a contrary conclusion that when markets function smoothly, policies that interfere with the functioning of those markets, such as price supports and input subsidies, perform poorly in terms of raising the incomes of farm households. They also suggest most of the benefits from input subsidies go to input suppliers and as savings are not passed fully on to farmers.

These debates also extended to the usefulness of fertilizer subsidies (Gulati and Kalra 1992; Gulati and Sharma 1995). Baker (1976) points out that a net gain in output can be obtained when fertilizer use is far below an optimal level due to lack of knowledge, risk aversion, and other reasons. Rosegrant and Herdt (1981) reveal a positive effect on production with an increase in fertilizer subsidies to rice farms in the Philippines. Ricker and Jayne (2010) find that wealth and social networks influence the effectiveness of a subsidy for anyone that receives it. Some research argues that subsidy policies might support unequal benefits because most of the profits are possibly absorbed by particular sectors and regions. Paul and Hrima (2010) indicate that the fertilizer subsidies were benefits concentrated on relatively few producers and regions in India. However, the estimation of the impacts of fertilizer subsidies in most of those researches is based on a descriptive analysis (e.g. Ricker , et al. 2010) or developed a simulation under the assumption of general equilibrium (e.g. Filipski , et al 2012). They ignore the structure and individual's behavior in an economic framework. Few results are provided to indicate how the benefits are allocated among those sectors, how much actually finds its way into the pocket of the farmer, and how much is siphoned away by the fertilizer suppliers. Similarly, few studies hold a discussion about who are the real beneficiaries of these subsidies, like small vs. large farmers, farmers vs. fertilizers suppliers, well-developed vs. less-developed regions, since the benefits have not been clearly delineated in many cases. Overall picture is not shown in the limited empirical studies. There is need to understand the fertilizer subsidy distribution pattern to assess whether the subsidy benefits the target groups.

The purpose of this research is to explore the distribution of welfare gains between farmers, fertilizer suppliers, and other sectors that result from a fertilizer subsidy policy. This question is applied to the Chinese rice production industry which consumed more than 60% of fertilizers in China. The analysis differs from previous studies in that the factor elasticity of substitution is not restricted to be zero, and a horizontal effect between fertilizer and non-fertilizer sectors is considered. In the next section, the history of the fertilizer industry and fertilizer subsidy policies in China is reviewed and a theoretical analysis of the subsidy's effect on the whole market is presented. Muth model is extended and applied to the Chinese rice industry to estimate the relative incidence and distribution of welfare among different sectors. The final sections conclude and draw some policy implications.

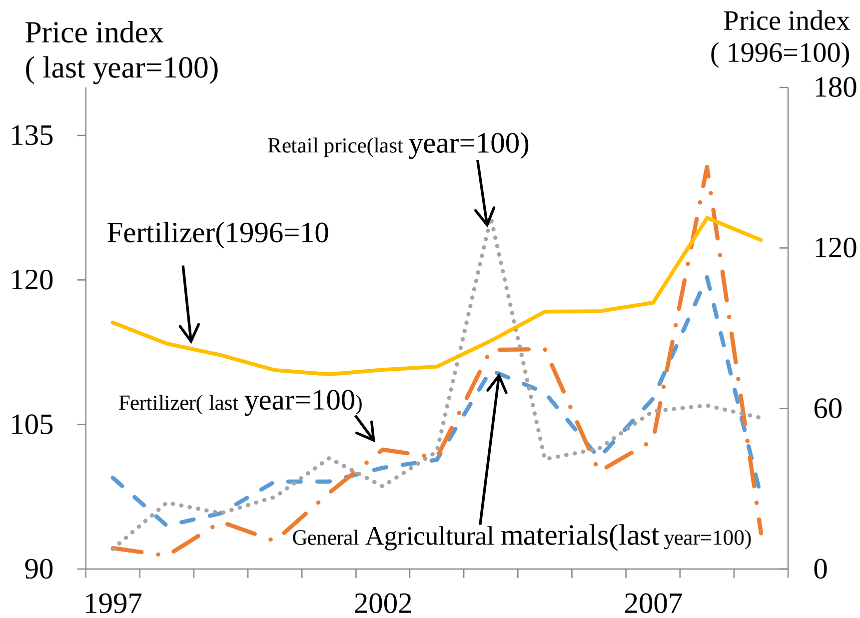
## 2. Fertilizer Industry and Fertilizer Subsidy Policy in China

China's fertilizer production has increased threefold since the 1980s, from 17.5 million tons in 1985 to 54.0 million tons in 2009 (Figure 3.1). Initially, the sale prices were fixed and controlled by the central government of China. But since 1998, restrictions on the market were loosened as a flexible price mechanism was introduced. The central government no longer determined the fertilizer's factory price but rather allowed the price to fluctuate within a certain range around a reference price; provincial governments even nearly opened the whole market and only limited the highest retail price. To compensate the increasing production costs for both fertilizer suppliers and farmers, subsidies have been provided to fertilizer companies in several ways, such as direct subsidies, reduced electricity price and transport costs, and lowing taxes. At the end of 2003, gross subsidies were up to RMB 60 yuans per ton, guaranteeing the fertilizer price without too much inflation (Figure 3.2).




Source: China Statistical Yearbook (2010)

Figure 3.1 Trends of fertilizer and rice production in China (1978-2007)




Source: China Statistical Yearbook (1996-2010)

Figure 3.2 Trends of fertilizer price index in China (1997-2007)

However, global prices of agricultural input materials, especially fertilizers, rose dramatically by the end of 2003. In order to reduce the farmers' burden and sustain the necessary rapid growth in the agricultural products supply, the central and provincial governments expanded the support policies, including production tax relief, transportation subsidies, and a reduced sale tax. By the end of 2004, fertilizer producers had received a tax credit of about RMB 56 yuans per ton, and RMB 6 billion yuans allowance was given in the fertilizer sector from a favorable electricity price. The direct subsidies for transportation reduced the factory's costs by RMB 6.19 billion yuans. In total, the relevant subsidies on fertilizer production were increased by 670%. Such a large subsidy raises an interesting question: who in particular benefits from these policies and by how much?

### 3. Economic Model in Multi-stage Market

To illustrate the effect of exogenous shocks on inputs in the multi-stage system, Baker's (1976) model is employed and extended in accordance to the analysis of Freebairn (1982) and Wohlgenant (1993). Consider three markets games in the system model simultaneously: the fertilizer market (Figure 3.3), the non-fertilizer market (Figure 3.4), and the output market (Figure 3.5). It is assumed that none of the producers and consumers has a power large enough to affect the market prices. Fertilizers are only used in a particular sector (e.g. rice industry) and the interactions affect the other sectors (e.g. corn industry) which are ignored in this analysis. In order to simplify the issues, both demand curves and supply curves are assumed to be linear. This simple model is shown in Figures 3.3-3.5.

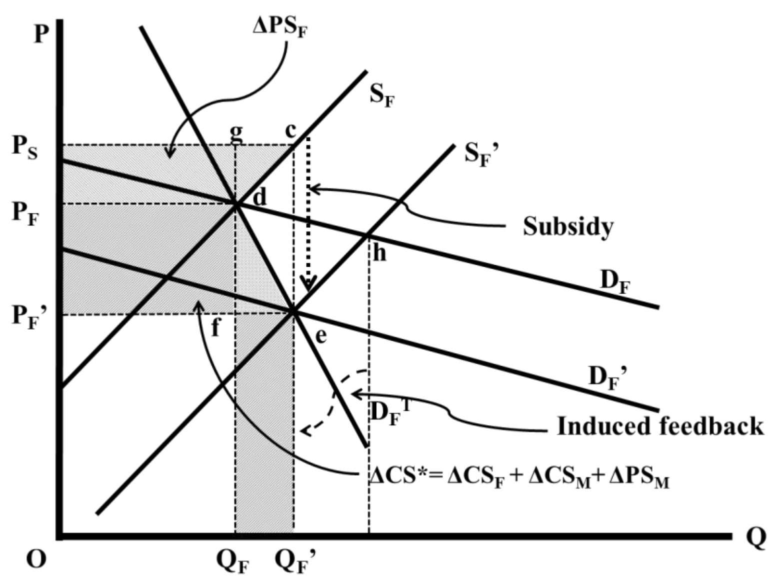



Figure 3.3 Model of fertilizer subsidy on fertilizer market

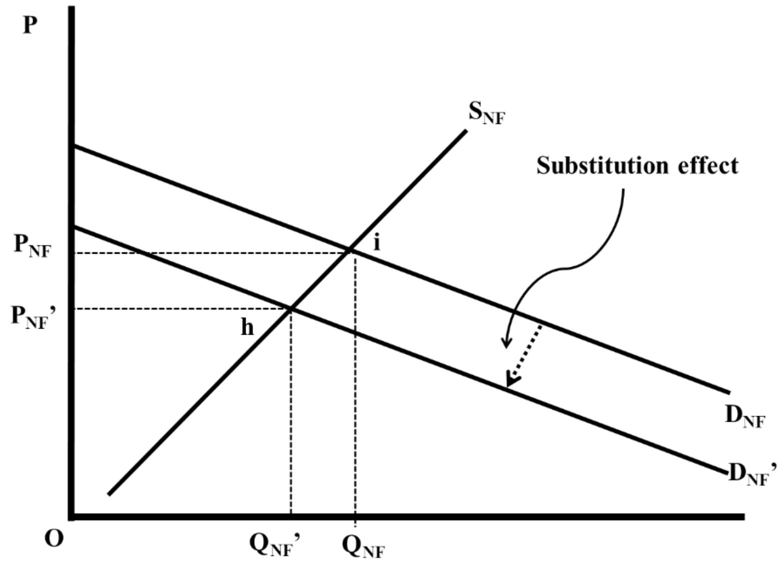



Figure 3.4 Model of fertilizer subsidy on non-fertilizer market

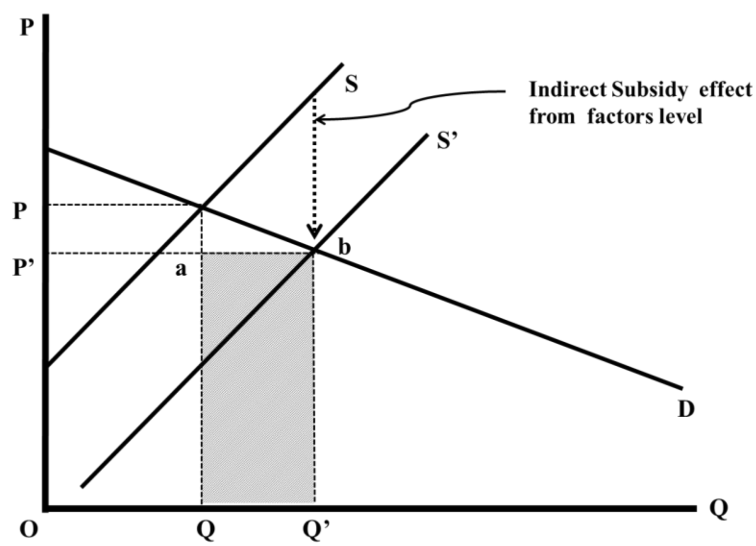



Figure 3.5 Model of fertilizer subsidy for rice market

We assumed the fertilizer market (Figure 3.3) is initially clear at point *d* where the farmers' demand ($D_F$) intersects the supply curve ($S_F$). The quantity produced and sold to farmers is $Q_F$ at the price of $P_F$. A subsidy to the fertilizer suppliers shifts the supply curve outward from $S_F$ to $S_F$'. Since the supply curve is the marginal cost curve, lower price and larger quantity will be derived at the new equilibrium point (*g*) after shifting the supply curve outward. Turning to the effect on non-fertilizer sectors (Figure 3.4) and assume it is a substituted goods respect to the fertilizer inputs. The price of non-fertilizer inputs would fall from $P_{NF}$ to $P'_{NF}$ due to the reduction of demand in non-fertilizer factors for which they are substituted. Meanwhile, the response from the reduction of price for non-fertilizer factors has a feedback effect to the fertilizer market and would push the fertilizer demand curve downward from $D_F$ to $D_F'$(Figure 3.3) (see more detail in Alston 1995 ). Finally, the 'total demand curve'[7] is derived as $D_F^T$ in response to the supply shift, and $D_F^T$ should be less elastic than the initial demand curve $D_F$ since the induced feedback effects from substituted goods.

A subsidy's pass-through influence on the output market is represented in Figure 3.5. More fertilizer is used in production because of a reduction in input (fertilizer) price, which incentives the farmers produce more and shifts the supply curves from *S* to *S'* and intersects demand (*D*) at point *b*. However, the magnitude of the vertical shift in output is not equal to that in fertilizer markets, but related to the incidence parameter of the subsides, which measures how much subsidy can be transferred from the input markets into the output markets.

As in Baker's (1976) analysis, the net gains from the policy can be separated into two parts: one is the growth of the fertilizer-producer surplus as represented by the area $P_sP_Fdc$, and the other is the growth of "gross" consumer surplus which can be shown with the area $P_FP_F'ed$ in Figure 3.3.This "gross" consumer surplus should include the change in consumer surplus in the fertilizer market and both consumer and producer surplus in the non-fertilizer market[8]. Particularly, farmers' net benefit is comprised of dual benefits minus a cost: the first benefit is

[7]Alston(1995, page 239) treated the "total" demand curve as "general" equilibrium demand curve that traces out the demand response to exogenous price changes in one market holding constant the supply curve for substitution goods.
[8] Alston (1999, page 239) defines gross consumer surplus as the change in consumer surplus measured off the general equilibrium demand for a good (the good is fertilizer in our study).

from buying the fertilizer at a lower cost as shown by the area of $P_F'fQ_FO$ in Figure 3.3; the second benefit is from the increased net output value, which is the extra revenue from output (area $abQ'Q$ in Figure 3.5); and the cost results from using additional amounts of fertilizer due to the favorable price (area $efQ_FQ$ in Figure 3.3).

It is straightforward to connect the above analysis with a Muth model (1964) which consists of vertically linked farm-level markets and factor markets. Indeed, the vertical relationship has been derived by many studies (Freebairn, et al., 1982;Alston and Scobie, 1983; Wohlgenant, 1989; Holloway, 1989; Alston, 1991; Wohlgenant, 1993; Alston, Norton and Pardey, 1995; Wohlgenant, 1999;Zhao, Anderson and Wittwer, 2003). In this chapter, it is assumed that the competitive input markets combine a fertilizer factor, $F$, and non-fertilizer factor, $M$ (including all other farm inputs and marketing inputs), to produce a homogeneous product, $Q$, with their prices being $P_F$, $P_M$, and $P$ respectively, under the condition of constant returns to scale (CRTS). A subsidy of $S^F$ ($S^M$) per unit is provided in the fertilizer industry (non-fertilizer industry) to raise production. The producers in both sectors are assumed to maximize profits. Trade is ignored since we assume the domestic market consumes a substantially large portion of production. Given the equilibrium displacement models (EDM) introduced by Muth (1964) and Gardner (1975), the change in equilibrium prices and quantities from shifts in input supply can be characterized as:

(1) $EQ = \alpha EF + \beta EM$

(2) $EQ = -\eta EP$

(3) $EP_F = -(\beta/\sigma)EF + (\beta/\sigma)EM + EP$

(4) $EP_M = (\alpha/\sigma)EF - (\alpha/\sigma)EM + EP$

(5) $EP_F = (1/\varepsilon_F)EF - \tau^F ES^F$

(6) $$EP_M = (1/\varepsilon_M)EM - \tau^M ES^M$$

where '$E$' indicates the relative change variables (e.g., $EQ = dQ/Q$). The system includes six endogenous variables $(Q, F, M, P, P_F, P_M)$, two exogenous variables $(S^M, S^F)$, and six parameters $(\eta, \varepsilon_F, \varepsilon_M, \alpha, \beta, \sigma)$. All parameters are assumed to be positive: both fertilizer supply elasticity $(\varepsilon_F)$ and non-fertilizer supply elasticity $(\varepsilon_M)$ are greater than zero; the input substitution elasticity $(\sigma)$ and absolute output demand elasticity $(\eta)$ are also with a positive sign. Furthermore, $\alpha = P_F F/PQ$ and $\beta = 1 - \alpha$ are set to be the cost share for $F$ and $M$. $\tau^F(\tau^M)$ is the subsidy ratio which is equal to per unit subsidy divided by fertilizer price (non-fertilizer price).

In this research, we are particularly interested in who benefits from the policies. Two methods are employed to assess the distribution of gains. Firstly, it is measured by the subsidy incidence, which is an economic term for the division of a subsidy or tax burden between buyers and sellers (Ruffle 2005). This is always used to measure the effect of a particular subsidy on the distribution of economic welfare (Harberger 1962; Howes and Murgai 2003; Zhao 2003; Ruffle 2005), although few studies applied this to a multi-stage market. Freebairn (1982) and Alston (1983) provide an explicit method to analyze tax incidence distribution in the multi-stage structure. Kinnucan and Paudel (2001) extend the tax incidences into two aspects: (1) incidences were calculated by considering the impacts in the overall inputs markets; and (2) incidences were calculated by only considering the impact in a particular input market. Following this method, the subsidy incidences were measured with two different perspectives:

*3.1 Subsidy incidence from the view of the overall inputs market*

Subsidy incidence estimation in this perspective is based on the view of the farm's supply in the output market. Dropping equation (2) to treat $P$ as temporarily exogenous and solving remaining equations simultaneously yield:

(7) $EQ = [(\varepsilon_F \varepsilon_M + \sigma\mu)/D]EP + [\alpha\tau^F \varepsilon_F(\varepsilon_M + \sigma)/D]ES^F + [\beta\tau^M \varepsilon_M(\varepsilon_F + \sigma)/D]ES^M$

Where $\mu = \alpha\varepsilon_F + \beta\varepsilon_M > 0$ and $D = \alpha\varepsilon_F + \beta\varepsilon_M + \sigma$>0. The coefficient for *EP* is positive for the given parameter in the general case, which indicates the normal supply curve is upward. The coefficients for $ES^F$and $ES^M$ are also positive, suggesting subsidies on both factors will shift the supply curve outward.

Setting $ES^M = 0$, the incidence parameter can be obtained by writing equation (7) in inverse form:$EP = 1/[(\varepsilon_F \varepsilon_M + \sigma\mu/D)]EQ - [\alpha\varepsilon_F(\varepsilon_M + \sigma)/(\varepsilon_F\varepsilon_M + \sigma\mu)]\tau^F ES^F$ (7b)

$ES^F$'s coefficient can simply be treated as $\tau^F\omega$, where $\omega$ is just the farmer's incidence parameter in the view of overall inputs; $EQ$'s coefficient could be written as $1/\varepsilon_Q$, where $\varepsilon_Q$ is the farmer's supply elasticity; and equation (7b) changes to:

(7c) $EP = (1/\varepsilon_Q)\, EQ - \tau^F \omega ES^F$

From equation 7b, the farmer's incidence ($\omega$) is determined by the parameters $\alpha, \beta, \varepsilon_M$,and $\sigma$. Farmers would obtain more only when $\omega > 1/2$, which is $\varepsilon_F\varepsilon_M(\alpha - 1) > \sigma(\beta\varepsilon_M - \alpha\varepsilon_F)$. Specifically, if fertilizer supply is perfectly inelastic ($\varepsilon_F = 0$), then $|\omega| = 0$, which means fertilizer suppliers would retain the entire subsidy. In contrast, if fertilizer supply is perfectly elastic, the farmer's incidence $|\omega| = \alpha(\varepsilon_M + \sigma)/(\varepsilon_M + \alpha\sigma) < 1$, suggesting only some of subsidies are passed through subsidy can be passed to the output market. It indeed shifts the farmer's supply curve outward in the output market but by a magnitude less than the fertilizer supply curve in the inputs market.

*3.2 Subsidy incidence from the view of fertilizer market only*

Subsidy incidence estimation in these perspectives only needs to consider the fertilizer demand in the inputs market. This could be derived by dropping equations (5) when $P_F$ is treated as exogenous, and solving the remaining equations simultaneously for $EF$, and then the derived demand curve for fertilizer is:

(8) $EF = -[(\varepsilon_M \lambda_F + \eta\sigma)/D'] EP_F - [\beta\tau^M \varepsilon_M(\sigma - \eta)/D'] ES^M$

where $\lambda_F = (\beta\sigma + \alpha\eta) > 0$ is the Allen market elasticity of derived demand and $D' = \varepsilon_M + \alpha\sigma + \beta\eta > 0$ (Bronfenbrenner 1961). The coefficient for $EP_F$ is expected to be negative, but the sign of $ES^M$ 's coefficient is uncertain. Fertilizer subsidies could generate positive or negative impacts for other input suppliers, depending on the relative magnitudes of $\eta$ and $\sigma$. In particular, a subsidy for fertilizer would reduce the demand for other inputs if $\sigma > \eta$, which means $F$ and $M$ are gross substitutes. Conversely, $F$ and $M$ are gross complements if $\sigma < \eta$ (Alston and Scobie 1983). In order to get the reduced-form elasticity of the gross fertilizer price with respect to the exogenous factor, substituting equation (8) into equation (5) yields:

(9) $EP_F = -\tau^F[\varepsilon_F/(\varepsilon_F + \eta_F)]\, ES^F + \varphi_M ES^M$

where $\eta_F = (\varepsilon_M \lambda_F + \eta\sigma)/D'$ is the farmers' "gross" demand price elasticity for fertilizer (the slope of $D_F^T$ in figure 3.3). Equation (9) indicates the net effect of the subsidy on the gross price of fertilizer. Based on equation (8) and equation (9), subsidy incidence for farmers can be quickly derived as follows：Let

(10) $P'_F = P_F + S^F$

where $P'_F$ is the net fertilizer price after subsidizing. Taking the total differential of equation (10) with respect to subsidy yields:

(11) $dP'_F/dS^F = dP_F/dS^F + 1 = {\tau^F}^{-1}(EP_F/ES^F) + 1$

where $EP_F/ES^F$ is the reduced-form elasticity of the gross fertilizer price with respect to the subsidy, which is $ES^F$'s coefficient in equation (9). Setting $ES^M = 0$ and substituting equation (9) into equation (11) yields:

(12) $dP_F'/dS^F = -[\varepsilon_F/(\varepsilon_F + \eta_F] + 1 = \eta_F/(\varepsilon_F + \eta_F)$

Denoting $\omega_F = |dP_F'/dS| = \eta_F/(\varepsilon_F + \eta_F)$, which is just the fertilizer suppliers' subsidy incidence when we focus is on the fertilizer market only. From equation (12), farmers would have more incidence from the subsidy when the elasticity of fertilizer supply ( $\varepsilon_F$) is greater than the gross fertilizer demand elasticity ($\eta_F$). The entire incidence would be shifted to the farmers if the fertilizer supply is perfectly elastic ($\varepsilon_F = \infty$) or gross fertilizer demand is perfectly inelastic ($\eta_F = 0$). Otherwise, fertilizer suppliers would receive the entire incidence if the fertilizer supply is inelastic ($\varepsilon_F = 0$) or the gross fertilizer demand is perfectly elastic ($\eta_F = \infty$).

### *3.3 Welfare distribution*

An alternative method to measure farmers' gain is to investigate the surplus distribution (Konishi 1990; Taylor and Martin 1997; Hamersma 2008). Alston (1995) provides a noteworthy statement about measuring welfare in the vertical market: "*The measurement of total benefits is not affected by the choice of where to measure the benefits in the marketing chain—the total producer and consumer surplus (or a total change in surplus) is the same at all market levels.*" Alston and Scobie (1983) applied this theory and concluded that the sectors that receive the investment (subsidies) will gain a larger share of total surplus when the inputs are substituted. They also suggested that farmers can even lose welfare if the inputs substitution elasticity is bigger than the demand elasticity for the product. In accordance to Alston's statement, welfare distributions are given by following:

(13) $\Delta CS^* = -P_F F \cdot EP_F(1 + 0.5EF)$

(14) $\Delta PS_F = P_F F(EP_F - B)(1 + 0.5EF)$

(15) $\Delta TS = \Delta CS^* + \Delta PS_F$

Specification:

(16) $\Delta PS_M = -P_M M \cdot EP_M[1 + 0.5E \cdot M]$

(17) $\Delta CS^* = \Delta CS_Q + \Delta PS_M$

In equation 14, $B$ is the vertical shift in the farm-level supply curve due to subsidy. $\Delta CS_i$, $\Delta PS_i$ and $\Delta TS$ represent the related changes in consumer, producer and total surplus, respectively. In particular, $\Delta CS^*$ is the gross consumer benefit, including the changes of total surplus in the non-fertilizer market and changes of consumer surplus in the fertilizer market.

Equation (17) can also be transformed as follows:

(18) $\Delta CS_Q = \Delta CS^* - \Delta PS_M$

where $\Delta CS_Q$ is the welfare change in the output market due to the shift in supply at farm level. $\Delta PS_M$ measures the quasi-rent that accrues in the non-fertilizer market. If gross substitution exists between $F$ and $M$, a subsidy would generate a negative externality in the $M$ sector ( $\Delta PS_M < 0$), but it also leads to a more positive externality in the output sector.

### *3.4 Farmers' welfare gains*

Alston (1995) mention that farmers' gains from fertilizer subsidies cannot simply be measured by consumer surplus in the fertilizer market because some contribution can be found in other sectors such as non-fertilizer sector and output sector. Kinnucan and Paudel (2001) introduced two alternative methods to compute the farmers' return in response to an increase in promotion. One way is to build a generalized "profit" function that takes into account vertical integration; the other is to measure farmers' "profit" by comparing the gains in producer surplus with the losses in producer surplus[9]. In this chapter, we employed the second most convenient method to estimate farmers' return as:

[9]Kinnucan and Paudel (2001, page 101-103) mentioned that "a common critique of farm programs is that the benefits are capitalized into land values, which implies that the major beneficiaries are initial landowners. The major beneficiaries of

(19) $\Delta PS_Q{}^F = PQ(EP - \omega_F B)(1 + 1/2EQ)$

where $\omega_F$ represents an incidence parameter that is bounded on the unit interval. For example, given the baseline values in table 3.1, $\omega_F$ = 0.25, which means that the subsidy to fertilizer causes a 25% vertical shift of the fertilizer supply curve.

## 4. Application to China's Rice Industry

To indicate the models' empirical utility, we applied the above models to China's rice industry, which is the largest fertilizer consumer. It is assumed that the industry is a closed economy since almost 99.4% of production is consumed in the domestic market according to (FAO 2004). Chen (2009) finds that farm technology in China exhibits constant returns to scale, thus, the assumption of CRTS in the industry is reasonable. Market power is ignored because no individual farmers could influence the market price.

### *4.1 Parameterization*

The parameters used in the empirical study are collected from the literature, which are defined in Table 3.1. The parameters $\eta$ and $\sigma$, are considered as a range: absolute value of rice own-price demand elasticity $\eta$ is set to 0.14, 0.35, and 0.4, estimating by Shen (2001) and Zhuang (2007). Since no estimates exist for the factor substitution elasticity $\sigma$, we follow the discussion in Wohlgenant (1989) and set $\sigma$ equal to 0.4, 0.6, and 1. Furthermore, the fertilizer supply elasticity is set to $\varepsilon_F$ =0.22, under the estimation of Chen (2009). The non-fertilizer supply elasticity is

promotion are the owners of fixed assets when the program was initiated (1987 in the case of catfish). New entrants receive little or no benefits in that they must pay higher prices for land and other fixed factors that appreciated in value. Moreover, new entrants must continue to pay the tax, or watch their asset values decline with the subsequent reductions in advertising."

aggregated and assumed to be 0.35. Finally, the input cost shares $\alpha$ and $\beta$ are calculated by 0.12 and 0.88, according to data from the China Statistic Yearbook (2004).

Table 3.1 Baseline values and parameters for China rice industry, since 2004

| Name | Description | Value |
|---|---|---|
| $\mathbf{Q}$ | Domestic demand of rice at the output level (million ton) | 135[a] |
| $\mathbf{P}$ | Product price of rice (RMB yuan/ ton) | 2600[b] |
| $\mathbf{F}$ | Fertilizer quantity (million ton) | 17.4[c] |
| $\mathbf{P_F}$ | Fertilizer price (RMB yuan/ ton) | 2175 [c] |
| $\mathbf{M}$ | None-Fertilizer quantity (million ton) | 154.5[d] |
| $\mathbf{P_M}$ | Non-fertilizer price (RMB yuan/ ton) | 1970[d] |
| $\mathbf{S^F}$ | Fertilizer subsidy (RMB yuan/ ton) before 2004 | 65[e] |
| $\mathbf{S^{F'}}$ | Fertilizer subsidy (RMB yuan/ ton) in 2004 | 500 [e] |
| $\boldsymbol{\tau}^{\mathbf{F}}$ | Fertilizer subsidy ratio ($S^F/P_F$) in 2004 | 0.03 |
| $\mathbf{S^M}$ | None-Fertilizer subsidy (RMB yuan/ ton) in 2004 | 30 [e] |
| $\boldsymbol{\tau}^{\mathbf{M}}$ | None-Fertilizer subsidy ratio ($S^M/P_M$) | 0.015 |
| $\boldsymbol{\eta}$ | Absolute value of rice own-price demand elasticity | 0.14[f],0.35[g],0.4[g] |
| $\boldsymbol{\varepsilon}_{\mathbf{F}}$ | Fertilizer supply elasticity | 0.22[h] |
| $\boldsymbol{\varepsilon}_{\mathbf{M}}$ | Other inputs supply elasticity | 0.35[h] |
| $\boldsymbol{\alpha}$ | Cost share of fertilizer | 0.12[i] |
| $\boldsymbol{\beta}$ | Cost share of other inputs | 0.88[i] |
| $\boldsymbol{\sigma}$ | Factors substitution elasticity | 0.4,0.6, 1 |

Note: [a] United States Department of Agriculture; [b] FAO statistic (2004); [c] China Statistic Yearbook (2005); [d] Calculate base on Cheng's study; [e] Fertilizer Market Report ,China (2008); [f] Shen ,2001; [g] Zhuang and Abbott ,2007; [h] Chen, *et al.*, 2009; [i] Calculate by author

*4.2 Simulation results*

The farmers' incidence allocations with the above mentioned parameters are given in Table 3.2. Fertilizer suppliers' incidence can be simply obtained as one minus farmers' incidence. Following the analyses in equation 7c and equation 12, incidence measured by considering the overall inputs are shown in the second column, while those estimations considering only the fertilizer market are shown in the third column. The results suggest that fertilizer suppliers are the biggest winner, gaining most of the incidence from the policies (73% to 84%) compared to 17% to 26% on average on the farmers' side. This implies that the gross fertilizer demand ($\eta_F$)

elasticity is higher than fertilizer supply elasticity ($\varepsilon_F$). Although this may be true in the short run in a closed economy, part of producers' incidence would be expected to pass to the farmers' side, as the fertilizer's supplier becomes more relatively elastic in the long run. If the market structure cannot be changed, a greater reliance on the fertilizer import market to reduce fertilizer demand elasticity or increase fertilizer supply elasticity might be a wise choice for improving the farmers' incidence.

Table 3.2 Allocation of Farmer's incidence, China Rice Industry, since 2004

| | Incidence (both inputs)[a] | Incidence (only fertilizer)[b] |
|---|---|---|
| **σ** =0.4 | | |
| **η** =0.14 | 0.21 | 0.09 |
| **η** =0.35 | 0.21 | 0.16 |
| **η** =0.4 | 0.21 | 0.17 |
| **σ** =0.6 | | |
| **η** =0.14 | 0.25 | 0.11 |
| **η** =0.35 (baseline) | 0.25 | 0.19 |
| **η** =0.14 | 0.25 | 0.20 |
| **σ** =1 | | |
| **η** =0.14 | 0.32 | 0.14 |
| **η** =0.35 | 0.32 | 0.26 |
| **η** =0.4 | 0.32 | 0.25 |
| Average | 0.26 | 0.17 |

Note: [a] Computed using text equations (7b'); [b] computed using text equations (12)

Sensitivity analysis is performed by varying the elasticity of substitution between farm input (σ), and output demand elasticity ($\eta$), as indicated in Table 3.2 holding other parameters constant. Farmers' incidence is suggested to be sensitive to the elasticity of input substitution, but the effects are modest. For example, in view of all the inputs, holding output demand elasticity equal to 0. 35, a rise in $\sigma$ from 0.4 to 1 causes farmers' incidence to increase from 0.21 to 0.32 in the second column, a 51% growth. A similar result is true from the view of the fertilizer sector. Farmers' incidence increases from 0.16 to 0.25, a 56% growth, as σ goes up from 0.4 to 1 in the third column. Comparatively, farmers' incidence is relatively insensitive to the output demand elasticity. The results are more extreme when incidence measured by considering the overall inputs, where the incidence is invariable as the demand elasticity changed. This implies that the output elasticity has no effect on the subsidy incidence. It can be shown from equation 7b that the incidence, $\omega$, equals $\alpha\varepsilon_F(\varepsilon_M + \sigma)/(\varepsilon_F\varepsilon_M + \sigma\mu)]\tau^F$. But, in the third column, the farmers' incidence would have a response to changes in demand elasticity (see equation 12). The incidence would be enlarged as the output demand elasticity increased, but the variations would be modest. This means changing the incidence by changing the demand elasticity in the output market is not a reality; instead, advisable adjustments on input substitution elasticity might yield some expected results.

Welfare measures based on the preceding formulas, presented in table 3.3, indicate that total benefit gains from a fertilizer subsidy policy are about RMB 7.6 to 7.8 billion yuans, which is slightly higher than the cost. The average benefit cost ratio (BCR) is about 1.3:1. The fertilizer supplier industry is also the largest beneficiary in this perspective, obtaining 70% of the total surplus. These profits are sufficient to offset the loss to the non-fertilizer suppliers due to the reduction of demand from the relatively higher price. The gross benefits, $CS^*$, range from RMB 1.5 to 2.9 billion yuans, which include changes for consumers and producers in the non-fertilizer market and changes for consumers in the fertilizer market. It is hard to distinguish how welfare is distributed in those three sectors, although we can obtain the change in quasi-rent that accrues in the non-fertilizer market, $\Delta PS_M$. $\Delta CS_Q$ is used to assess the welfare change in the output market due to the shift in supply at the farm level. The value of $\Delta CS_Q$ is significantly greater than the gross benefit ($CS^*$), which implies the subsidy would generate a negative externality in the non-fertilizer sector since gross substitution exists in the two inputs.

Similarly, sensitivity analysis is performed by setting the input substitution elasticity and output demand elasticity to alternative values. Results show that the total surplus ($\Delta TS$) are robust to changes in σ and $\eta$. As the substitution elasticity or output demand elasticity become more elastic, total surplus only increase slightly. For example, given a constant $\eta$=0.35, a rise in $\sigma$ from 0.4 to 1 causes total surplus to improve from RMB 7.67 billion yuans to RMB 7.9 billion yuans, a 0.3% growth; and, while holding $\sigma$=0.6, total surplus increases from RMB 7.68 billion yuans to RMB 7.69 billion yuans as the demand elasticity goes up from 0.14 to 0.4, only 0.05% growth. In contrast, fertilizer suppliers' benefits ($\Delta PS_F$) are much more sensitive to $\sigma$, although it still has a small response to changes in output demand elasticity. Therefore, the share of benefits to fertilizer supply is more sensitive to $\sigma$ but robust to $\eta$. For instance, given the parameters in the baseline, fertilizer suppliers' gains increase by 25% from RMB 4.9 billion yuans to RMB 6.1 billion yuans and share increases 16% from 64% to 80% as $\sigma$ becomes more elastic. In contrast, while the impacts of a rise in output demand elasticity on fertilizer suppliers' gains and share are both less than 4%.

The subsidy for non-fertilizer suppliers ($\Delta PS_M$) seems to be an inferior instrument in the sense that it generates an average loss of 0.8 RMB billion yuans. This loss could be reduced by increasing the output demand elasticity. When $\eta$ increases to equal the elasticity of input substitution, the loss will disappear (see the result when $\eta = \sigma = 0.4$). This implies that a loss from the substitution effect in the inputs market can be compensated by increasing demand in the output market. In contrast, a raise of $\sigma$ might increase the loss in non-fertilizer suppliers since the relatively higher substitution elasticity would largely shift the demand curve downwards in the non-fertilizer market, which raises their price and reduces the quantity. Even though the demand inflation in the output market may enhance the demand in both inputs markets, the small increment due to inelasticity in output demand, might not be sufficient to digest the loss in the non-fertilizer market.

Table 3.3 Welfare Distribution of 670% Increase in the Fertilizer Subsidy, China Rice Industry, Since 2004 (Billion Yuan)

| Item | Subsidy Effect | Share | Subsidy Effect | Share | Subsidy Effect | Share |
|---|---|---|---|---|---|---|
| SC1: $\boldsymbol{\sigma}$ =0.4 | η =0.14 | | η =0.35 | | η =0.4 | |
| $\mathbf{CS}^{*a}$ | 2.91 | 0.38 | 2.75 | 0.36 | 2.72 | 0.35 |
| $\mathbf{\Delta CS_Q}$ | 4.20 | 0.55 | 2.92 | 0.38 | 2.72 | 0.35 |
| $\mathbf{\Delta PS_F}$ | 4.75 | 0.62 | 4.92 | 0.64 | 4.95 | 0.65 |
| $\mathbf{\Delta PS_M}$ | -1.28 | - | -0.17 | -0.02 | - | - |
| $\mathbf{\Delta TS}^{b}$ | 7.67 | 1 | 7.67 | 1.00 | 7.67 | 1 |
| SC2: $\boldsymbol{\sigma}$ =0.6 | η =0.14 | | η =0.35 | | η =0.4 | |
| $\mathbf{\Delta CS}^{*}$ | 2.31 | 0.30 | 2.1.5 | 0.28 | 2.13 | 0.28 |
| $\mathbf{\Delta CS_Q}$ | 4.03 | 0.53 | 2.81 | 0.37 | 2.61 | 0.34 |
| $\mathbf{\Delta PS_F}$ | 5.37 | 0.70 | 5.53 | 0.72 | 5.55 | 0.72 |
| $\mathbf{\Delta PS_M}$ | -1.72 | -0.22 | -0.64 | -0.08 | -0.48 | - |
| $\mathbf{\Delta TS}$ | 7.68 | 1 | 7.68 | 1.02 | 7.69 | 1 |
| SC3: $\boldsymbol{\sigma}$ =1 | η =0.14 | | η =0.35 | | η =0.4 | |
| $\mathbf{\Delta CS}^{*}$ | 1.69 | 0.22 | 1.54 | 0.20 | 1.52 | 0.20 |
| $\mathbf{\Delta CS_Q}$ | 3.86 | 0.50 | 2.68 | 0.35 | 2.51 | 0.33 |
| $\mathbf{\Delta PS_F}$ | 6.01 | 0.78 | 6.15 | 0.80 | 6.1. | 0.80 |
| $\mathbf{\Delta PS_M}$ | -2.17 | - | -1.13 | -0.15 | -0.98 | - |
| $\mathbf{\Delta TS}$ | 7.69 | 1 | 7.70 | 1.00 | 7.70 | 1 |

Note: [a]$\Delta CS^{*} = \Delta CS_Q + \Delta PS_M$; [b]$\Delta TS = \Delta CS^{*} + \Delta PS_F$

The mean return to farmers is about RMB 2.5 billion yuans, capturing about 30% of total surplus (table 3.4). In this case, farmers' gains should include the benefits from the fertilizer sector since both suppliers and consumers are benefited by the subsidy policy. It also contains a benefit from the output market. The effect on the non-fertilizer market cannot be ignored, although it may be positive or negative. Unfortunately, it is not possible to calculate them separately, rather we have to measure them as a bundle. Those results are based on a conventional measurement which would fail to account for farmers' integration into processing.

A drawback in the analysis of farmers' gain, mentioned by Kinnucan and Paudel (2001), is that farmers' benefits calculated by 'profit' do not take into account the subsidy scheme's general equilibrium effects, which may lead to misleading results with respect to the actual impacts of the subsidy on farmers.

Increase the values of σ and $\eta$ are both in favor of the farmer's return. However, the adjustments are robust to $\eta$ but relatively sensitive to $\sigma$. For example, given a constant elasticity of input substitution of 0.6, increasing $\eta$ from 0.14 to 0.4 causes the short-term net quasi-rent accruing to the farmers to rise from RMB 2.0 billion yuans to RMB 2.2 billion yuans, a mere 10%. But increasing σ from 0.4 to 1 causes the farmers' gain to rise from RMB1.8 billion yuans to RMB 3.0 billion yuans, which is almost 67% of total surplus. This is also true by the fact that output demand elasticity is less than the input substitution elasticity.

Table 3.4 Farmers' Return to Fertilizer Subsidy, China Rice Industry, since 2004 (RMB billion yuan)

| | Subsidy Effect [a] | Share [b] | Subsidy Effect | Share | Subsidy Effect | Share |
|---|---|---|---|---|---|---|
| | η =0.14 | | η =0.35 | | η =0.4 | |
| SC1:**σ**=0.4 | 1.56 | 0.2 | 1.76 | 0.23 | 1.79 | 0.23 |
| SC1:**σ**=0.6 | 2.03 | 0.26 | 2.22 | 0.29 | 2.25 | 0.29 |
| SC1:**σ**=1 | 2.81 | 0.37 | 2.99 | 0.39 | 3.02 | 0.39 |

Note: [a] Subsidy Effects are calculated according to equation 20. [b] Shares are generated by dividing by the value ΔTS in Table 3.3.

Comparing the gains between farmers and fertilizer suppliers, the subsidy policy is more favorable to the latter. The farmers' experience of less rent dissipation is not only due to this sector's inelastic supply response ($\varepsilon_F < \eta_F$), but also to the subsidy externality. In particular, the lower price for fertilizer associated with the increasing subsidy would reduce the demand for non-fertilizer inputs, since σ < η, which confers a cost to the non-fertilizer sector. Consequently, the fertilizer sector collects double benefits: one from the direct subsidy, and the other from the non-fertilizer sector's feedback effect. However, the total net benefit remains constant no matter how the elasticities change, indicating the principle that changes to elasticities in supply and demand indeed affect a sector's incidence, but not the total welfare impacts.

*4.3 Alternative policies*

The analysis so far suggests that fertilizer supply sector, capturing almost two-thirds of the benefit from the subsidy policy, is the biggest beneficiary. A separate question is whether the benefits can be redistributed with different policies, given a constant amount of total subsidy. Under the assumption of fixed elasticities in the short run, a conventional alternative action is to reallocate the subsidies in different sectors. In this chapter, we only consider reassigning the subsidy within the inputs sector. Four potential policy actions are examined with differing subsidy proportions in the two input sectors. These policy actions are: (a) the fertilizer sector obtains two-thirds of the total subsidy while the remaining part is given to the non-fertilizer sector; (b) the two input sectors halve the subsidy; (c) the fertilizer sector obtains one-third of the total amount while the remaining part is given to the non-fertilizer sector; and (d) the entire subsidy is shifted to the non-fertilizer sector.

Table 3.5 reports the results of welfare analyses for different scenarios given the parameters in the baseline (=0.35, $\sigma$=0.6, $\varepsilon_F$=0.22, and $\varepsilon_M$ =0.35). As expected, reallocations of subsidies in the inputs sectors have larger effects welfare distribution. In general, shifting subsidy to non-fertilizer sectors would transfer most of the returns from fertilizer suppliers to non-fertilizer suppliers. However, the total surplus and the farmers' gain are undetermined. For instance, if half of all subsidies are transferred to the non-fertilizer sector, fertilizer suppliers' gain would decrease more than a half, from RMB 5.5 billion yuans to RMB 2.3 billion yuans. Part of the benefit will go to the farmers, around RMB 1.2 billion yuans, and part of the benefit will go to the non-fertilizer suppliers, around RMB 2.4 billion yuans. Besides, part of deadweight/efficiency losses can be compensated by slightly enlarging the total surplus by RMB 0.12 billion yuans.

Farmers' gains reach a maximum of RMB 3.3 billion yuans when one-third of the total subsidy is transferred to the non-fertilizer sector. But as the quantity increases, farmers' gains begin to shift down. Total surplus are maximized in the scenario when only one-third of all subsidies remain in the fertilizer sector. However, the shares to the fertilizer suppliers and farmers are only 25% and 38% respectively, and much of the benefits are absorbed by the non-fertilizer suppliers.

Table 3.5 Welfare Measures in Different Subsidy Polices, China Rice Industry, since 2004 (RMB billion Yuan)

| Scenarios | Nome-Fertilizer supplier | Fertilizer supplier | Share | Farmers | Share | **ΔTS** |
|---|---|---|---|---|---|---|
| Baseline(All of subsidies on fertilizer sectors) | -0.65 | 5.53 | 0.78 | 2.22 | 0.31 | 7.1 |
| (a) 2/3 of subsidies on fertilizer sectors | 0.99 | 2.74 | 0.39 | 3.25 | 0.47 | 6.9 |
| (b) Half of subsidies on fertilizer sector | 1.87 | 2.3 | 0.32 | 3.05 | 0.42 | 7.2 |
| (c)1/3 of subsidies on fertilizer sectors | 2.74 | 1.86 | 0.25 | 2.84 | 0.38 | 7.4 |
| (d) All of subsidies on non-fertilizer sectors | 4.48 | - | - | 1.89 | 0.03 | 6.3 |

The analysis does not imply that the existing subsidy policy is not efficient, but at least it is not the optimum. A specific goal to either maximize farmers' benefit, or maximize total surplus, or balance the benefits in particular sectors, should always be known by the policy makers during the whole process, from policy designing to implementation. In this case, if the subsidy policy was initially designed to ease the burden of the rice farmers, there are obvious preferable choices than the existing one.

## 5. Discussion and Conclusion

Historically, it is suggested that the improvements to soil fertility by increased fertilizer use can stimulate agricultural productivity, improve food security, and increase rural income (Crawford et al. 2003). Fertilizer subsidies were considered particularly important in inducing farmers to increase production and yields. Therefore, with increased in fertilizer use over time, fertilizer subsidies have also increased.

China's government has provided a large amount of funding annually to improve farmers' income. However, it seldom considers who actually receives the benefit. Results from this analysis suggest fertilizer suppliers receive the most benefit, obtaining 70% of total surplus. This distribution would be difficult to change in the short run since the market structures are fixed. Yet, another question is whether these allocations are efficient. So far, it is not possible to answer yes or no because the government did not exactly quantify the goal of subsidizing fertilizer in regard to the benefit brought about by the policy. For farmers, they pay more attention to maximizing their profits regarding to subsides. If most the returns are being captured by supplier as our finding, the policy will reduce their profits. Farmers might have the incentive to make a change in the long run, once they realize the unbalanced benefit distribution from the subsidies.

From a welfare perspective, both farmers and fertilizer suppliers are benefited by the favorable subsidy policy since they can gain RMB 2.2 billion yuans and RMB 5.3 billion yuans, respectively. This distribution can be changed as the subsidy is transferred to the non-fertilizer sector, but the sector's benefit seems to hardly be in accordance to the total welfare. This requires policy makers to make decisions according to their strategies: what is a priority and how to balance the benefits in the sectors.

Some researchers also challenge whether it is necessary to subsidize fertilizer (Hedley 1989; Xu 2009; Banful 2011). Chinese fertilizer production had increased by 20% in the post-subsidy years, from 45 million tons in 1998 to 54 million tons in 2009. Is the increase in the amount fertilizer necessary? Guo (2010) gives a negative answer in discussion of acidification in major Chinese croplands. His study reports that there is a diminishing marginal rate of return to fertilizer in China and even the marginal rate is negative in most areas because of over acidification resulting from a history of excessive fertilizer use. It is also suggested that cutting fertilizer use in half won't change the crop's quantity or quality. If the conclusions hold, the subsidy actually only motivates fertilizer suppliers to over-produce. There may be few incentives for farmers to increase fertilizer use when the inputs have already been saturated under their budget constraint. They would not increase the use of fertilizer—even if the price goes to zero—when they find the negative marginal rate of return to fertilizer.

In conclusion, these analyses challenge the fertilizer subsidy policy. More importantly, environmental externalities from fertilizer use are ignored in this chapter, and this issue is attracting more and more of the public's attention. Some studies have begun to investigate the possibility of part of the fertilizer subsidies being withdrawn or removed (Gladwin 1992; Miguel 2008). However, the removal or withdrawals of the subsidies are still to be challenged because it might increase the farmers' production cost. This is a dilemma for policymakers: if they keep the subsidy, it may increase the government's burden and exacerbate negative externalities; but if they reduce or remove the subsidy, it might bring a negative effect on farmers in the short run. Therefore, some scholars suggest moving parts of fertilizer subsidies from fertilizer industry to the non-fertilizer sectors. This chapter presents some framework and empirical results for different political scenarios for further investigation.

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