ABSTRACT

DEAL, JOHN L. The Empirical Relationship Between Federally-Subsidized Crop Insurance and Soil Erosion. (Under the direction of Duncan M. Holthausen and Barry K. Goodwin).

This study examines the impact of federally-subsidized crop insurance and government program payments on soil erosion. Specifically, this study analyzes the impact of those programs on production decisions, such as acreage allocation and input use, and the resulting impact on soil erosion. The first essay investigates the "conventional wisdom" that economically marginal land is also environmentally fragile (i.e., highly erodible). We address this issue by looking at the distribution of crop yields across erodibility classes and by performing regression analysis. Our results indicate that land with higher levels of soil erodibility exhibit lower mean crop yields, a proxy for economic marginality, which lends support to the conventional wisdom. The second essay investigates the impact of federally-subsidized crop insurance on acreage allocation and input use in the primary cotton growing regions in the United States. Using county-level data from the 1990-1995 and 1996-2000 time periods, we find that the acreage response to insurance participation, though statistically significant, is quite inelastic. The results of simulations that we conducted indicate that large premium rate reductions would generate significant changes in insurance participation, but those changes would not result in large changes in planted acreage. The third essay investigates the relationship between specific government agricultural programs and soil erosion. Using county-level data from the years 1992 and 1997, we estimate a model of soil erosion and crop insurance participation. We find that crop insurance participation and conservation payments are significantly associated with county average soil erosion levels, while other program payments, e.g., deficiency and AMTA payments, exhibit no statistically significant association with our soil erosion measure.

The Empirical Relationship Between Federally-Subsidized Crop Insurance and Soil Erosion

by

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To my mother Nora Jenkins

Biography

John Deal was born on September 19, 1955 to Luther and Nora Deal in Statesville, North Carolina. After graduating from South Iredell High School in 1974, John began attending UNC-Charlotte in the fall of 1974. He received a Bachelor of Science degree in Political Science in May of 1979. Having received his degree, John spent the next fifteen years working in the food service industry. After deciding to return to school, he completed the course requirements for a M.S. degree in economics from UNC-Charlotte. He then enrolled in the Ph.D. program at N.C. State University in 1997.

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Chapter 1

Introduction

Concerns about the potential environmental problems, such as nonpoint-source pollution, associated with agricultural production practices have become more prevalent in policy debates and the environmental/economics literature. In particular, concerns have been raised as to the impact of agricultural subsidies and risk management policies, such as federally-subsidized crop insurance, deficiency payments, and ad hoc disaster relief payments, on production choices. If farmers alter their production choices in a manner that leads to increased agricultural pollution, these programs may yield unintended consequences for environmental amenities, such as clean air and water. In addition, these policies may work at cross-purposes with other government policies, such as land retirement programs, designed to reduce agricultural pollution.

In particular, concerns have been raised as to the impact of federally-subsidized crop insurance on the acreage allocation decisions made by farmers. If crop insurance lowers the risk associated with planting, farmers may be encouraged to expand production, particularly on marginal land that may not be economically viable without the reduction in risk. The conventional wisdom is that economically marginal land is also environmentally fragile, as evidenced by higher levels of soil erodibility. Therefore, expansion of production to economically marginal land may also shift production to highly erodible land. This expansion in production may also be associated with the destruction of land cover and buffer areas that protect water sources from agricultural sediment and chemical run-off. If differences in crop coverage benefits and costs encourage farmers to switch production to crops that require a greater degree of land cultivation, this may also tend to exacerbate agricultural pollution problems.

An expansion of total crop acreage due to the reduction in production risk raises the possibility that aggregate chemical use will also increase. If production is shifted toward more chemical-intensive crops, agricultural pollution may be amplified beyond the level solely associated with the expansion in acreage. On the other hand, moral hazard concerns would suggest that the reduction in risk may encourage farmers to reduce their use of chemicals. Since agricultural chemical (i.e., pesticide and herbicide) and fertilizer use is often cited as a major source of nonpoint-source pollution, the direction and magnitude of the aggregate change in chemical/fertilizer use associated with the provision of crop insurance is central to an understanding of the impact of crop insurance on agricultural pollution.

Recent research into the impact of crop insurance on production decisions has often yielded contradictory results. Keeton, Skees and Long (2000) found substantial acreage increases due to the availability of crop insurance, while Goodwin, Vandeveer and Deal (2004) found relatively small production increases in response to large insurance premium rate reductions. In reference to the impact of crop insurance on input use, Wu (1999) found that the availability of crop insurance led to an increase in chemical expenditures, while Smith and Goodwin (1996) found that the availability of crop insurance led to a reduction in chemical expenditures. While both of these issues have received a great deal of recent attention, there has been no conclusive resolution to these questions and, as a result, they still warrant further research.

While researchers have addressed the impact of crop insurance on acreage and input use decisions, little research has been conducted to evaluate the impact of changes in acreage allocation and input use on measures of environmental change. It has generally been assumed that increases in production and input use lead to adverse environmental outcomes (e.g., increases in soil erosion and water pollution). While direct measures of environmental amenities, such as water quality, are available on a limited basis, soil erosion has been found to be highly correlated with other negative environmental outcomes, such as groundwater pollution and increased sediment levels in streams and rivers. Agricultural practices (e.g., plowing and discing) remove cover vegetation and break down soil structure, which increases the incidence of soil erosion. This leads to an increase in the likelihood of chemical and sediment displacement, which increases the likelihood that water quality and other environmental amenities will be reduced.

The conventional wisdom that economically marginal land is also environmentally fragile has rarely been questioned. Therefore, it is generally assumed that any government policy that encourages farmers to plant on economically marginal land will lead to production on environmentally marginal (i.e., highly erodible) land. If economically marginal land is not highly correlated with erodible land, then possible acreage expansion due to the provision of crop insurance or other government income support policies may have limited environmental costs. In one of the few attempts to address this issue, Heimlich (1989) concluded that the correlation between economically marginal and environmentally marginal land was “extremely weak” (p.14). This calls into question the conventional wisdom that crop insurance-induced acreage expansion would necessarily harm the environment.

We address a number of questions in this study. First, we explore the relationship between economically marginal and environmentally marginal land. We use crop yields as a proxy for economic marginality and the soil erodibility index reported in the National Resources Inventory (NRI) as a measure of soil erodibility. To address this issue, we look at the distribution of crop yields across classes of soil erodibility. If the conventional wisdom holds, crop yields should decline as the level of soil erodibility increases. In addition, we conduct a more detailed analysis by regressing crop yields on the erodibility index and a set of conditioning variables.

Second, using county-level data from two time periods (1990-1995 and 1996-2000), we look at the impact of the provision of federally-subsidized crop insurance on cotton acreage allocation and chemical/fertilizer expenditures within the primary cotton growing regions of the United States. Within the context of addressing these two questions, we also explore the determinants of crop insurance demand. In addition, we look at the impact of a number of government program payments, such as loan deficiency payments and Agricultural Market Transition Act (AMTA) payments, on acreage response during the 1996-2000 period.

Finally, we look at the impact of the provision of crop insurance and other government program payments on the level of soil erosion in counties that specialize in the production of corn, soybeans, and winter wheat. Combining county-level government payment data and soil erosion measures from the 1992 and 1997 NRI datasets, we estimate a model of soil erosion and insurance participation within an instrumental variables framework. Soil erosion is a function of land characteristics, climate, land use, management practices, and conservation efforts. We model soil erosion primarily as a function of the determinants of land use, including net market returns, government program payments, and crop insurance participation.

The remainder of this chapter is organized as follows. The next section provides a brief discussion of the government policy environment facing the farmer during our period of study (1990-2000). We briefly discuss the details of the agricultural price support and risk management policies that contributed to the environment in which the farmer made production decisions during this period. The final section provides a discussion of the National Resources Inventory (NRI). A brief discussion of the NRI is warranted since we make extensive use of the NRI data in our exploration of each of the questions addressed in this study.

1.1 Government Policy Environment

Since the Agricultural Adjustment Act of 1933, the federal government has intervened in agricultural markets to control the supply of agricultural commodities, stabilize farm income, and reduce the risk associated with output and price uncertainty. To aid in the stabilization of farm income, the federal government has provided nonrecourse loans, deficiency payments, land diversion payments, and marketing loans. To control commodity supplies and market prices, the federal government has mandated acreage reduction and set-aside requirements for participation in commodity payment programs. It also has required farmers to maintain a base acreage in program crops to be eligible for program payments and provided rental payments for farmers who retired erodible land from production. In addition, the crop insurance and disaster relief programs reduce the production risks associated with environmental factors beyond the control of the farmer. The overall impact of these programs has been to reduce the farmer's response to market signals and provide a potential incentive for farmers to produce on economically marginal land.

Until the passage of the Food, Agriculture, Conservation, and Trade Act of 1990 (FACT), federal agricultural policies were focused on: (1) removing land from production to control commodity supplies and prices and (2) providing support payments in the event of low market prices. Nonrecourse loans were made available where farmers could pledge their stored commodities as collateral to obtain loans from the Commodity Credit Corporation (CCC). If the market price was higher than the loan rate (plus interest), the farmer could sell the crop and pay off the loan, but if the market price was less than the loan rate (plus interest) the farmer could forfeit the commodity as the means of payment. Forfeiture would occur when commodity prices were low, so the removal of the commodity from the market would increase the market price.

To eliminate the accumulation of commodity stocks associated with the forfeiture option, the marketing loan program was introduced for rice and upland cotton in 1986.[1] The marketing loan program allowed farmers to enjoy the benefits of the income support without actually arranging a loan. If the posted county price (PCP) is less than the loan rate (LR), the farmer can receive a loan deficiency payment (LDP) equal to the difference between the PCP and LR without having to take out a commodity loan. In other words, the LDP ensures that the grower will receive a minimum payment (i.e., the loan rate) for each unit of eligible production (Wescott and Price 2001).

In addition, farmers could receive deficiency payments on program crops (wheat, corn, grain sorghum, barley, oats, upland cotton, and rice) in the event of low prices. The deficiency payment rate was based on the difference between the target price and the higher of the average national market price or loan rate. In addition to the loan rate, the total deficiency payment was based on the base acreage that was eligible for production.[2] Since the deficiency payment was tied to the base acreage of the program crop, this encouraged overproduction in an effort to build the base acreage and discouraged substitution to non-program crops which would reduce the base acreage. To be eligible for these payments, farmers were required to set-aside a percentage of their total planted acreage for conservation use and idle a percentage of their base acreage in the Acreage Reduction Program (ARP). Farmers also could receive diversion payments for voluntarily removing land out of production, though this was generally not a requirement for eligibility in other income support programs.

In an effort to allow farmers more planting flexibility, FACT allowed farmers to plant other crops on 25% of the program-crop base acreage without reducing the base acreage. On 15% of the acreage (i.e., normal flex acres), they would receive no deficiency payments regardless of the crop planted. On the remaining 10% (i.e., optional flex acres), deficiency payments would continue if the program crop was planted, but would be eliminated if another crop was planted. As a result, some switching occurred on normal flex

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[1] The program was extended to soybeans and other oilseeds in 1991 and to wheat and feed grains in 1993.

[2] The base acreage was calculated as the average of acreage planted to a program crop over the previous five year period. A higher base acreage was associated with higher deficiency payments. Since this encouraged overproduction of the program crop, the Food and Security Act of 1985 mandated that overproduction of the base acreage would make the farmer ineligible for the receipt of deficiency payments.

acres, but little switching occurred on optional flex acres (Lin, Westcott, Skinner, Sanford and Ugarte 2000). CCC nonrecourse loans and the target price system were continued under FACT.

Substantial changes occurred with the passage of the Federal Agricultural Improvement and Reform Act of 1996 (FAIR). The 1996 Act eliminated the target price support system and granted farmers almost complete planting flexibility. Farmers who participated in the wheat, feed grain, cotton, and rice programs in any year between 1991 and 1995 were made eligible for Agricultural Marketing Transition (AMTA) payments. These payments were to be disbursed over a seven year period and capped at approximately $ 36 billion over that period. AMTA payments replaced the target price deficiency based system and were decoupled from production decisions since the farmer was allowed to receive payments for acreage planted to any crop other than fruits and vegetables. In addition, payments were based on historical base acreage and soybeans were added as a program crop. Farmers were not allowed to update their base acreage, so these payments should be decoupled from current planting decisions.[3] To be eligible for these decoupled payments, farmers were required to meet conservation compliance requirements and maintain the land in agricultural use (including idling) during the period of the program. The marketing loan program was continued and loan deficiency payments have replaced target price-based payments as a means of income support for the farmer. In addition, low market prices in 1998 and 1999 led to the provision of ad hoc Market Loss Assistance (MLA) payments to compensate for low prices.

As early as the Agricultural Adjustment Act of 1938, some form of yield crop insurance has been made available to farmers to reduce the risk associated with weather, pest infestation, plant disease and other detrimental environmental factors. The present system is a public-private partnership where the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA) designs and rates federal crop insurance policies that are then sold and serviced by insurance companies in the private sector. In addition, the RMA provides subsidies to farmers to offset actuarially fair premium rates, shares potential losses with insurance companies, and provides partial funding for the administrative costs associated with crop insurance delivery.

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[3] A number of researchers (see Hennessy (1998); Goodwin and Mishra (2003), for example) have questioned whether or not these payments are actually decoupled from current production decisions. Specifically, they have raised the possibility that these payments may impact production decisions through wealth effects or through the loosening of credit constraints.

The oldest and most widespread form of crop insurance is Multiple-Peril Crop Insurance (MPCI).[4] MPCI protects farmers against yield losses due to natural causes such drought, hail, insects, and excessive moisture. Yield coverage levels are based on the expected yield of the commodity which is determined by the actual production history of the farm for the insured crop.[5] The expected yield is constructed as the mean of the last 4 to 10 years (if available) of actual farm crop yields. The farmer selects a yield coverage level, ranging from 50% to 75% of the expected yield in 5% increments.[6] The farmer also selects an indemnity price, ranging from 55% to 100% of the expected crop price estimated by the RMA. If the actual yield falls below the insured yield (APH yield times the selected yield coverage), the farmer receives an indemnity payment equal to the indemnity price times the difference between the insured yield and the actual yield (Vandeveer and Young 2001).

In 1994, the Crop Insurance and Reform Act (CIRA) was enacted to extend crop insurance coverage in an effort to improve the actuarial performance of the program and to reduce the reliance on ad hoc disaster payments. CIRA established catastrophic (CAT) coverage in addition to "buy-up" APH coverage. CAT coverage pays 55% of the indemnity price when actual yields fall below 50% of expected yields. This coverage is provided to farmers for a small administrative fee. The 1994 Act also provided higher premium subsidies for the APH buy-up coverage and linked the receipt of other government support payments to the purchase of at least CAT coverage. While farmers were required to purchase a minimum of CAT coverage in 1995 to ensure continued eligibility for other agricultural payments, the FAIR Act of 1996 repealed this requirement if farmers waived their right to future ad hoc disaster payments (Vandeveer and Young 2001).

While MPCI covers growers against yield shortfalls, it failed to protect against unfavorable movements in crop prices. As a result, farmers still faced revenue volatility. Beginning in 1996, revenue insurance policies were issued for some crops and some geographic locations. There were three basic revenue insurance plans - Crop Revenue Coverage (CRC), Income Protection (IP), and Revenue Assurance (RA) - that were made available during the 1996-2000 period of this study. All of the plans extended traditional MPCI coverage to include protection against price variability, though each differed in the details

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[4] MPCI differs from traditional private market insurance since it is designed to protect against losses that result from a variety of sources, while most private market policies protect against losses from one source, such as hail or fire.

[5] This form of MPCI is also known as Actual Production History (APH) insurance.

[6] The coverage level can be as high as 85% for selected crops in selected locations.

of the plan. Rapid expansions in revenue insurance coverage have taken place in the last few years. Though yield and revenue insurance has substantially reduced the production and price risk facing the grower, the federal government has still continued to provide ad hoc disaster relief payments.

In summation, recent changes in agricultural policy have, at least in principle, attempted to reduce the degree of government intervention in agricultural markets without increasing the variability of farm income. While planting constraints and current production-based subsidy payments have been eliminated (or reduced), government intervention still takes place in the form of loan deficiency payments, AMTA payments, crop insurance premium subsidies, and ad hoc payments, such as disaster relief and MLA. Given the importance of government agricultural policies on the production decisions made by farmers, we endeavor to take them into account in our analyses.

1.2 National Resources Inventory Data

This study makes extensive use of data collected in the National Resources Inventory (NRI). The NRI is a longitudinal panel survey conducted by the USDA National Resources Conservation Service (NRCS). The NRI collects detailed data on the condition of the nation's soil, water, and other natural resources on all nonfederal lands and water areas within the 48 conterminous United States. The data are collected every five years (since 1977) from over 800,000 sample sites. This study uses the data from the 1982, 1987, 1992, and 1997 surveys.[7] Among other things, the NRI survey contains data on soil characteristics (e.g., land slope), land cover and use, predicted soil erosion, wildlife habitat, and conservation practices. The NRI data are based on recognized statistical sampling techniques and can be reliably aggregated to national, regional, state, and sub-state levels.[8] In addition, the NRI data set is constructed so that it can easily be linked to other databases, such as the Soils Interpretation Record (SIR) data collected by the NRCS.

One of the major uses of the NRI data is to evaluate the impact of public policy (e.g., the Conservation Resource Program) on the present and future conditions of the

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[7] The most recent version (1997) contains revisions in the earlier data so that they are consistent with the sampling techniques employed in the most recent survey.

[8] See Fuller (1999) for a detailed discussion of the validity of the statistical techniques employed in the NRI.

nations's resource base. To facilitate the study of the impact at various levels of aggregation, the NRI contains an element ($xfact$) that is used to aggregate the data. The $xfact$ specifies the number of acres that a sample point represents. To make sure that the weights accurately represent the size of all sample sites within a county, the $xfact$ weights for all of the sample points in a county sum to the total surface area of the county. This assures that the importance of the results gathered at one sample point are adjusted to account for differences in the amount of land that each sample point represents. In the aggregation process, a measure of soil erodibility estimated at a site representing 20 acres of land will be given twice the weight of another measure of soil erodibility at another site which represents only 10 acres of land. In this study, we use both sample sites and counties as units of observation. The sample site data require no weighting, while the county-level aggregation requires use of the weighting factor.[9]

While the NRI does not include measures of the actual level of soil erosion, it contains data on variables that are considered to be factors that contribute to changes in long-term levels of soil erosion. For example, the Universal Soil Loss Equation (USLE) is used to predict long-term average annual soil loss associated with sheet and rill (i.e., water-induced) erosion. The USLE contains measures of soil erodibility, slope length, slope steepness, and soil permeability. In addition, the USLE includes measures that capture the cropping and conservation practices employed on the land. Data on all of these factors are collected and reported in the NRI. In addition to containing variables used directly in the estimation of soil erosion, the NRI contains many other variables, including soil erodibility, soil loss tolerance, and rainfall erosivity, that have an impact on the physical environment facing the farmer. This wealth of data on land characteristics and climatic factors allows us to condition production decisions on the environmental factors facing the grower.

This study contains five chapters. In addition to providing a brief presentation of the issues under consideration, this chapter provides a brief review of the government policy regimes within which farming decisions were made during our period of study and the NRI data employed in this study. Chapter 2 presents an investigation of the relationship between economically marginal land and environmentally fragile land. Chapter 3 presents

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[9] It should be noted that concerns about the accuracy of aggregating NRI data to the county level have been raised by the National Resources Conservation Service (NRCS). Goodwin and Smith (2003) point out that aggregating other data collected at the county level, such as crop yields and government payment data, to higher levels of aggregation, such as major land resource areas (MLRAs), may introduce even more severe aggregation problems.

an investigation of the impact of federally-subsidized crop insurance on the production decisions (acreage allocation and input use) made by farmers in the major cotton producing regions of the United States. Chapter 4 presents an investigation of the impact of federally-subsidized crop insurance and government program payments on levels of water-induced soil erosion in major corn, soybean, and winter wheat producing areas in the United States. The final chapter provides a summary of the findings in the previous chapters.

Chapter 2

The Relationship Between Economically and Environmentally Marginal Land

2.1 Introduction

Recent research undertaken to explore the relationship between government programs, e.g., crop insurance, and acreage allocation decisions (see Wu (1999); Goodwin et al. (2004), for example) was motivated, in part, by concerns that increases in acreage or changes in input use would lead to a decline in environmental amenities. It has generally been assumed that the reductions in production risk associated with the availability of insurance and income subsidies encouraged production on economically marginal land. In this context, economically marginal land can be thought of as land that would not be cultivated at current output and input prices without the availability of government support programs. The "conventional wisdom" is that economically marginal land is also environmentally fragile, i.e., highly erodible (Goodwin et al. 2004). This assumed positive correlation between economically marginal land and environmentally fragile land has rarely been questioned. In one of the few attempts to address this issue, Heimlich (1989) concluded that there was a relatively weak correlation between economically and environmentally marginal land.

For given output and input prices, land productivity (i.e., potential crop yield) determines whether or not land should be considered economically marginal. If input prices decrease, output prices increase, or the provision of government programs reduces production risk, economically marginal land may be brought into production. If this land is also highly erodible, the increase in cultivated cropland will potentially lead to greater levels of soil erosion, habitat destruction, and water quality degradation. As a result, the environmental impact of the provision of government income support and risk reduction programs depends on the direction and the magnitude of the link between economically marginal and environmentally fragile land.

It has generally been assumed that land retired from production due to its inherent erodibility or erosion history will not entail the sacrifice of high levels of production since erodible land is thought to be less productive than nonerodible land.[1] If there is not a significant negative relationship between land erodibility and productivity, efforts to take highly erodible land out of production (e.g., the Conservation Reserve Program (CRP)) could result in higher levels of foregone production than originally thought. As a result, the opportunity costs, in terms of foregone production, incurred by society when attempting to reduce soil erosion will again depend on the direction and magnitude of the link between economically and environmentally marginal land.

In a comprehensive study of the relationship between risk management policies and environmental outcomes, Soule, Nimon and Mullarkey (2000) concluded that “the hypothesis that economically marginal land is also environmentally marginal is largely untested” (p.2) and that “research efforts need to be broadened to determine the environmental vulnerability of economically marginal cropland” (p.26). The limited research conducted in this area occurred primarily during the 1980s. Recent changes in federal risk management programs (e.g., increases in federal crop insurance subsidy levels) provide increased incentives for farmers to expand crop acreage on economically marginal land. If the land brought into production is also environmentally fragile, these policies may result in higher levels of environmental damage. Therefore it is increasingly important to explore the relationship between economically and environmentally marginal land.

Contrary to the concerns expressed by many (see Plantinga (1996)) as to the susceptibility of less productive land to soil erosion, one can also provide a reasonable argument that less productive land may be less susceptible to soil erosion (i.e., less erodible). For example, lower land productivity may result from low levels of soil permeability which inhibits the transport of water from rainfall to the rooting zone of the plant. As a result,

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[1] In addition to the inherent erodibility of the soil, the impact on productivity will also depend on the tolerance of the land to soil loss. Our measure of erodibility includes the T factor, the measure of tolerance to productivity decreases due to soil loss.

one would expect to obtain lower crop yields. At the same time, lower soil permeability is associated with lower levels of soil erosion since less permeable soils, such as clay, are less susceptible to wind- or water-induced soil erosion. Therefore, it is theoretically possible that less productive land may be associated with less erodible soil. While "conventional wisdom" would indicate that economically marginal land (i.e., land with lower productivity) should also exhibit higher levels of soil erodibility, this is an open empirical question that deserves study.

The potential environmental impact of land brought into production can be seen by looking at differences in soil erodibility by changes in land use. Table 2.1 contains the mean soil erodibility levels of land brought into cultivation during the period from 1982 to 1997.[2] The table designates the land use prior to cultivation and the data indicates the level of soil erodibility as measured after the land was brought under cultivation.[3] Noncultivated cropland and pasture that was brought into cultivation during this period exhibited higher levels of soil erodibility than land that remained under cultivation during the period.[4] For example, pasture brought into production during the 1982-1987 period exhibited a level of soil erodibility that was almost twice as large (15.8609 vs. 8.0736) as the land that remained under cultivation from 1982 to 1987. It is likely that the increases in soil erodibility associated with the cultivation of previously noncultivated cropland and pastureland reflect initial efforts, such as plowing, needed to prepare the land for planting. If agricultural risk management policies encourage farmers to bring pasture and noncultivated cropland into cultivation, this will increase the mean soil erodibility of land under cultivation, at least during the initial periods of cultivation.

This study attempts to explore this relationship by extending the framework employed by Heimlich (1989). To capture the idea of economic marginality, we equate this concept with land productivity. As with Heimlich's study, we use crop yields as a measure of productivity. In contrast to Heimlich, we look at the yields of multiple crops in our study. In

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[2] The changes in land use designation are contained in the National Resources Inventory. The NRI contains a number (recordid) that allows one to link data from multiple points in time to one sample site. While data exists at five year intervals, these changes do not take into account changes that may have occurred during the five year inventory period.

[3] The NRI does not provide measures of erodibility for land (e.g., pastureland) that is not designated as cropland (cultivated or noncultivated) or Conservation Reserve Program land. While the erodibility index was therefore not available for the beginning land use for pastureland, alternative analysis of cultivated and noncultivated cropland indicates that the soil erodibility index values were similar when using the previous or ending year measure.

[4] Noncultivated cropland includes land used for horticulture (e.g., fruit or nuts), grass/hay/legume rotations, or land not used for crop production (e.g., corn or cotton) during the previous three years.

Table 2.1: Soil Erodibility by Land Use Change

Previous Land Use	*Soil Erodibility*		
	1982-1987	1987-1992	1992-1997
Cultivated	8.0736	7.6931	9.2827
Noncultivated	11.8492	11.8115	16.7845
Pasture	15.8609	13.5452	26.5619

addition, we also employ a measure of production variability (i.e., the coefficient of variation of county average yield) to proxy for economic marginality. Heimlich used a measure of soil erodibility (the Erodibility Index) based on the factors contained in the Universal Soil Loss Equation (USLE).[5] While the erodibility index employed by Heimlich only accounted for water-induced erodibility, we also take into account the impact of wind-induced erodibility in our study.

We employ two methodological approaches in our study. First, we analyze the distribution of crop yields and crop yield variability across different levels of erodibility. A finding that mean crop yields decrease as erodibility levels increase would lend support to the conventional wisdom, while a finding that crop yield variability increases as erodibility levels increase would also lend support to the conventional wisdom. Second, we employ multiple regression analysis to determine the contribution of our measure of soil erodibility to the variation in our measures of land productivity. We also include measures of inherent land productivity, climate, and management practices to capture other factors that affect crop yield and yield variability. While many of these factors are relatively stable over time, they can often exhibit a high degree of cross-sectional variability. We employ data from the 1992 NRI and the SOILS-5 data (see section 2.4 for more detail) in this study. Since the study uses data from one year only, all of the variation in the model is cross-sectional.

This study is organized as follows. Section 2 provides a discussion of the relevant literature. Section 3 presents the methodology employed to test the relationship between economic and environmental marginality. In addition, we also discuss the theoretical issues associated with the measures of economic and environmental marginality employed in this study. Section 4 presents a discussion of the data, while a presentation and discussion of the results is provided in section 5. A summation of the findings and concluding remarks are presented in the final section.

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[5] The USLE predicts the long-run average soil loss associated with runoff from fields with specific characteristics and under specified cropping and conservation practices.

2.2 Literature

As previously stated, there has been very little research conducted to explore the relationship between productivity and soil erodibility. In an early effort, Bills (1985) examined the relationship between the yields for two crops - corn silage and hay - and the level of soil erodibility on New York cropland. He used both SOILS-5 and state generated estimated crop yields in the study.[6] Using the $RKLS$[7] components of the Universal Soil Loss Equation (USLE) to define the inherent physical capacity of the soil to erode, he found that SOILS-5 yields for both crops exhibited a weak negative correlation (ranging from -.093 to -.106) with the level of soil erodibility.[8] In addition, Bills used the $RKLS$ measure to develop 3 classes (nonerodible, moderately erodible, and highly erodible) of soil erodibility. Using the SOILS-5 data, he found that mean crop yields were quite similar across all erodibility classes. For example, corn silage yields were 20.3 tons per acre on nonerodible land and 20.6 tons per acre on highly erodible land. His results failed to support the conventional wisdom that highly erodible cropland is not very productive.

Reganold and Singer (1984) looked at the relationship between two land classification systems - the USDA land capability classification (LCC) system and the Storie index - and input/output ratios for farms in California's San Joaquin Valley.[9] The input/output ratios proxied for the productivity of the land, while the two classification systems proxied for the erodibility of the soil. They hypothesized that higher quality lands would have lower input/output ratios (expressed as dollar of inputs per dollar of output) than would lower quality lands. This approach tests the relationship between land productivity and soil erodibility only if there is a strong positive correlation between land classes and soil erodibility. While the USDA land classification system consists of eight classes, they consolidated the classes into two categories representing prime (1.0-3.0) and nonprime (3.01-6.0) farmland. They calculated I/O ratios for each crop in the study and for all combined crops.

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[6] Soil Interpretation Record (SOILS-5) data is a collection of soil survey attribute information. Among other things, it contains information on physical and chemical soil properties, land use, and estimated crop yields. This data can be linked to the NRI sample sites by a key or pointer (nriptr) contained in both datasets.

[7] The $RKLS$ components of the USLE account for the soil and climate variables that affect potential soil erosion. The R variable accounts for the impact of rainfall and runoff on potential soil erosion, the K variable accounts for inherent soil erodibility, and the L and S variables account for the impact of slope length and steepness on potential soil erosion.

[8] The correlations with the state generated estimates were slightly higher, ranging from -.311 to -.339.

[9] The Storie index is a land classification system developed in California that is based on the physical characteristics of the land.

For the aggregated crop data, they found that lower (1.0-3.0) LCCs exhibited significantly lower I/O ratios than higher (3.01-6.0) LCCs. When analyzing individual crop data, they found the same pattern for all crops except cotton, though the differences were small in magnitude. They concluded that the results were driven by the relationship between output and land capability class, i.e. prime farmland exhibited substantially higher output than nonprime farmland, while exhibiting only slightly higher input costs.[10] The relationship between land capability and the I/O ratio was not as strong when the Storie index was employed. In particular, the aggregate crop data I/O ratios were not significantly different for the six classes of the Storie index.

Heimlich's study (1989) is the most comprehensive effort to date to explore the relationship between land productivity and erodibility. In addition, his basic approach forms the starting point of the approach employed in this study. As a result, a detailed discussion of his methodology and results is warranted. Heimlich's purpose was to test the "hypothesis that highly erodible soils are less productive than less erodible soils and empirically investigate the overlap between physically and economically marginal U.S. cropland" ((Heimlich 1989), p.1.). He used data from the 1982 NRI survey and the Soil Survey Interpretations Record (SOILS-5) to obtain productivity and soil erodibility measures.[11] The study was national in scope since it used all nonirrigated sample points in the NRI data where at least one of the eight crops used in the study was grown.

His methodological approach consisted of presenting the correlations between measures of productivity and soil erodibility, the distributions of productivity measures by erodibility levels, and regression results obtained by regressing measures of productivity on measures of erodibility. He used the Bills-Heimlich soil erodibility classification system as the measure of soil erodibility.[12] He used corn grain yield and average net revenue from field crops as measures of soil productivity.[13] Dummy variables for USDA land capability

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[10] Intuitively, one would think that the higher LCCs, i.e., lower quality land, would have higher input costs, e.g., costs associated with land clearing and irrigation. Their result that lower LCCs had higher input costs was largely driven by the higher costs associated with weeding and harvesting.

[11] The SOILS-5 data contains estimated crop yields that can be linked to NRI site data. This allows the researcher to avoid aggregating the NRI data to a level, e.g. county, where crop yield data is available. The crop yields in the SOILS 5 data are estimated to approximate "leading commercial farmers at the management level that tends to produce the highest economic returns per acre" (Heimlich 1989). Therefore the estimated yields may be slightly larger than those obtained over a wide range of farm sizes and management practices.

[12] The Bills-Heimlich classification system used the $RKLS$ components of the USLE to partition cropland into three classes - highly erodible, moderately erodible, and nonerodible - based on its physical characteristics and the type of cropping activities conducted on the land.

[13] The net revenue measure was calculated as the gross revenue of eight major field crops minus their

classes and subclasses and USDA prime farmland designation were included in the regression equations as independent variables to proxy for measures of inherent land productivity.

In the correlation results, Heimlich found that the relationship between the Bills-Heimlich erodibility measure and both productivity measures (i.e., corn yield and net revenue) was negative and not significantly different from zero (-.110 and -.059, respectively). While the signs were consistent with the hypothesis that less erodible land is more productive, the magnitudes of the correlations were relatively small. He also found a weak and negative relationship between land capability class and both productivity measures. The relationship between the prime farmland designation and both productivity measures was positive, but also weak. In terms of the independent variable correlations, the Bills-Heimlich measure of soil erodibility was not highly correlated with either of the inherent land productivity independent variables, with a .318 correlation with USDA land capability classes and a -.187 correlation with the USDA prime farmland designation.

When analyzing corn grain yield by level of erodibility and land capability class, Heimlich found that yields were higher on nonerodible land for land capability classes 1-3, but were lower (except for wind erodible land) for capability classes 4-8. Even in capability classes 1-3, crop yields were almost as high (96 bushels/acre) on moderately erodible land as on nonerodible land (99 bushels/acre). The same pattern held when analyzing corn yields by erodibility and prime farmland designation. For example, corn yields on nonprime farmland in the moderately erodible class (83 bushels/acre) were higher than those in the nonerodible class (76 bushels/acre). Similar results were generated when net crop revenue was used as the measure of productivity. Results for both measures of productivity indicate that the conventional wisdom that productivity is lower on highly erodible lands may not be accurate.

Heimlich used multiple regression analysis to decompose the impact of soil erodibility classifications on productivity. Specifically he regressed the two measures of productivity on the following independent variables: Bills-Heimlich soil erodibility classes, USDA land capability classes, USDA land capability subclasses, and the USDA prime farmland designation. The measures of inherent land productivity (i.e., the prime farmland designation and the class/subclass designations) were included to capture the impact of land characteristics,

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variable costs of production. This measure was employed as an alternative to corn yields since previous research indicated that crop yields on the same land are often not highly correlated. Therefore the use of one indicator crop may bias the results to the degree that it may not represent the yield-land erodibility relationship for all crops.

excluding land erodibility, on the dependent variables. The independent variables were all discrete categorical variables that were represented by dummy variables. The coefficients on these regressors indicated how much that attribute added or subtracted from mean crop yield and net revenue. The estimated yields were generated by summing the coefficient estimates on each regressor.

In general, highly erodible land added more to corn grain yield and net revenue than did nonerodible land. Highest yields were generated on highly erodible land, while lowest yields were generated on wind erodible land and nonerodible land. For example, nonerodible land added 137.3 bushels to corn grain yield, while highly erodible land added 142.4 bushels. Land capability subclass e where potential soil erosion was deemed to be the primary limiting factor to agricultural production subtracted 12.5 bushels from corn grain yields. While this e subclass result lends support to the view that erodible land is less productive, the results for the land capability classes were not as definitive. For both measures of productivity, land capability classes 1-3 exhibited higher productivity than classes 4-8, but productivity did not decrease for each increasing class level. For example, land in LCCs 4 and 5 subtracted more from corn grain yield than did land in LCCs 6 and 7.

Even though the multiple regression approach employed by Heimlich is a step in the right direction (compared to the simple correlation methods of other studies), there are a number of problems with the regression equations used in his study. First, all of the independent variables measure the same general underlying physical land characteristics. Although the correlations between the independent variables range from -.187 (prime farmland to the Bills-Heimlich erodibility classes) to -.620 (prime farmland to the USDA land capability classes), the fact that they measure the same underlying physical properties raises concerns about the existence of multicollinearity. In addition, Heimlich failed to include other variables - input use, temperature, rainfall, and technology - that have been found to be important determinants of crop yield.

In a study of the use of productivity measures to target conservation programs, Runge, Larson and Roloff (1986) compared a measure of erosion potential, i.e., land erodibility, with a measure of land productivity. Runge et al. used the Bills-Heimlich measure of soil erodibility, while the productivity index was constructed to incorporate the factors that lead to suitable root growth.[14] They conducted their study for six Major Land Resource

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[14] The adequacy of root growth is considered to be essential to potential plant growth. Among the factors

Areas (MLRAs) in the Midwest using 1982 NRI and SOILS-5 data. While MLRAs with low erosion potential generally had high values for the productivity index, the third highest value for the productivity index occurred in a MLRA with the most erodible land. In addition, the most productive land was not found in the MLRA with the least erodible land. Exploring the relationship between air pollution and crop yield, Westenbarger and Frisvold (1995) found a negative relationship between corn and soybean yields and the Bills-Heimlich measure of soil erodibility.

While the previously discussed research addressed the productivity-erodibility relationship directly, studies of other research questions have generated results that are pertinent to this question. In an exploration of the impact of soil conservation programs in the Palouse region of Washington, Young, Walker and Kanjo (1991) divided land into two general categories - nonerodible and highly erodible - based on an erodibility measure constructed as the ratio of the RKLS factors from the USLE and the soil loss tolerance levels T.[15] The highly erodible land was then subdivided according to the level of productivity based on soil properties. They presented correlations between crop yield estimates for winter wheat, spring barley, and dry peas and their land class categories. They found that nonerodible land generated higher crop yields than erodible land with moderate or low productivity, but erodible land with high productivity generated the highest crop yields. This result was consistent across crops and subregion divisions within the Palouse region.

Studying the impact of management practice (e.g. types of tillage and crop rotation) on crop yield, input use, and soil erosion, Wu and Babcock (1998) found that the relationship between corn yields and land quality measurements was inconsistent. The USDA land capability class measure exhibited a negative relationship with corn yields in 6 of the 8 management practice combination scenarios under study. While this could lend support to the belief that less erodible land (i.e., lower LCC levels) exhibits higher productivity (i.e., higher crop yields), the coefficients on the LCC variables were insignificant at the 10% level in 7 of the 8 management practice scenarios. In terms of significance, similar results were found for other measures of soil quality, including the slope of field and soil clay percentage.[16]

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included in the productivity index were the sufficiency of available water capacity and the sufficiency of bulk density.

[15] The T value denotes the maximum rate of annual soil erosion that could occur without significantly diminishing crop productivity. High tolerance values are assigned to soils that exhibit the adequate rooting depth and soil properties that are required for successful crop growth.

[16] A field with a high percentage of soil clay is less susceptible to soil erosion than land with more finely

In summary, the sparse research that has been conducted concerning the relationship between economic and environmental marginality has yielded inconsistent results. Most of the research has involved the use of simple correlation procedures. Other studies using more sophisticated econometric techniques (Wu and Babcock 1998) have not addressed this issue directly. In the most comprehensive direct study of this issue, Heimlich failed to take into account differences that may exist across crops and geographic regions. In addition, the crop yield equation estimated by Heimlich failed to explicitly account for a number of the determinants of crop yield, such as management practices. Little research has been conducted during the last decade to take advantage of improvements in the statistical reliability of the NRI data used in many of these studies. Given greater data reliability, the potential environmental impacts of government policy-induced expansions in production, and the potential opportunity costs associated with acreage reduction programs, this relationship deserves a more comprehensive and updated analysis.

2.3 Methodology and Estimation

2.3.1 Measures of Economic Marginality

The first step in undertaking this study is the development of empirical measures of economic and environmental marginality. The concept of economic marginality is state dependent. Land that could not be economically cultivated under some level of output (input) prices and policy regimes may come under cultivation under some other price and policy regime. Holding prices and government policies constant, an increase in the productivity of the land increases the likelihood that a particular field will be brought into cultivation. Assuming that price and policy changes are not specific to geographic location, differences in economic marginality across space would be highly dependent on differences in land productivity. Since the data used in this study varies across space (not time), differences in land productivity will determine which land should be identified as economically marginal. Possible measures of land productivity include the following: (1) the economic returns to the land, (2) the average crop yield, and (3) the variability of the crop yield. We employ mean crop yield and crop yield variability as our proxy measures for economic

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textured soil.

marginality in this study.[17]

While Heimlich used one indicator crop yield (i.e., mean corn yield) to proxy for land productivity, different crops exhibit complex interactions with soil characteristics and climate that vary during the period of the growing season. In particular, different crops may require different types of soil for growth. For example, corn and soybeans grow best on high-quality finely-textured soils, while wheat grows best on deep fertile soils (Wu and Segerson 1995). By looking at only one crop, it may be difficult to capture the different impacts of soil erodibility on crop productivity across different types of soil. Motivated by this potential concern, we include equations to model mean yield for the following crops: corn, soybeans, cotton, and grain sorghum. The inclusion of these four crops ensures that a variety of different soil types and characteristics are included in this study.

The mean crop yield data we use in this study comes from two different sources - SOILS-5 estimated crop yields and NASS county-level crop yields. Following the approach employed by Heimlich, we use the SOILS-5 estimated mean crop yields in the site-specific portion of our study. This data was collected and analyzed by the USDA's Soil Conservation Service (SCS), which later became the Natural Resources Conservation Service (NRCS). In addition to collecting data on estimated crop yields, the NRCS collects data on soil characteristics (e.g., texture, organic matter content, and water holding capacity), climate characteristics (e.g., mean rainfall and temperature), and physiographic characteristics (e.g., slope and land cover) for individual soil mapping units.[18]

The crop yields are estimated for a series of benchmark soils. Yield estimates for other soils are then made by comparing the key soil properties (e.g., pH levels and water holding capacity) of the soil in question with the soil properties of similar benchmark soils. In addition, differences in climate between the mapping units are taken into account when assigning estimated yields to each site. These soil property comparisons and the estimated crop yields are based on the judgments of soil scientists, agronomists, and conservationists. A number of sources of crop yield information are used to develop the SOILS-5 yield estimates for the benchmark soils. These estimates are based on yield measurements from all of the following: (1) commercial farm fields, (2) field trials for particular farming prac-

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[17] Differences in crop yield and yield variability may result from differences in the physical, chemical, and biological characteristics of the soil. It may also capture substitution of other inputs, e.g., fertilizers, for land.

[18] A soil mapping unit is a collection of areas that are defined in terms of their soil components or miscellaneous areas, where miscellaneous areas are areas that contain no recognizable soil but share common observable surface features, such as rock formations and vegetation.

tices, and (3) small research plots at experiment stations and other research institutions. Crop yields are estimated for soils on which the particular crop is most commonly grown.[19] Attempts are made to employ ten years of data, if available, when estimating crop yields.

Crop yields are estimated assuming that the farmer employs a high level of management. The National Soil Survey Handbook defines a high level of management as "a level obtained by leading farmers that produce the highest economic returns per acre. It includes the best varieties; balancing plant populations and added nutrients to the potential of the soil; control of erosion, weeds, insects, and diseases; maintenance of optimum soil tilth; adequate soil drainage; and timely operations."[20] Given the level of management assumed for the crop yield estimates, those yield estimates should represent the upper end of the yield distribution.

NASS county-level mean crop yields are used for the aggregate portion of our study.[21] While these yields are not directly attributable to the individual NRI sample points (and thus may mask the heterogeneity between sites), they are constructed from historical crop yield data, and thus provide an alternative to the SOILS-5 estimated crop yields. Unlike the SOILS-5 data, the NASS data can also be used to develop a measure of yield variability. The variability of crop yields can be thought of as a measure of land productivity, and thus economic marginality. If crop yields are more variable on a particular plot of land, the associated production (and thus revenue) risk make it less likely that a risk-averse farmer will cultivate the plot.

Since two sources of crop yield data are employed in this study, a comparison of the summary statistics of the two measures is warranted. Table 2.2 provides summary statistics comparing the NASS mean crop yields (N) and the SOILS-5 estimated crop yields (S). To provide a direct comparison to the NASS data, the SOILS-5 data were aggregated to the county level before the calculation of the summary statistics.[22]

Differences are readily apparent when comparing the NASS and SOILS-5 data. While the SOILS-5 yields were estimated to reflect the implementation of a "high" level of management, and therefore should reflect the upper end of the yield distribution, the

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[19] Crop yields are not reported on soils where they are too low to be economically feasible or where they are economically feasible but not competitive with other potential crops (Heimlich 1989).

[20] The National Soil Survey Handbook acts as a guideline for soil scientists when collecting soil samples, measuring soil characteristics, and estimating crop yield data.

[21] A brief description of NASS data collection methods can be found at the USDA website address http://www.usda.gov/nass/nassinfo/estimate.html.

[22] The SOILS-5 crop yields can be linked to each NRI site and then aggregated to the county level by the use of the NRI weighting factor ($xfact$) which accounts for the acreage represented by each NRI site.

Table 2.2: Comparison of NASS and SOILS-5 Mean Crop Yields

Crop	*Summary Statistics*				
	Obs.	Mean	St. Dev.	Median	Correlation
Corn(N)	2490	91.3699	25.9118	89.4100	.2661
Corn(S)	1724	90.3162	30.9964	95.4650	(.0242)
Cotton(N)	624	544.3834	197.0318	537.7506	.5627
Cotton(S)	366	552.5802	211.0526	599.5283	(.0532)
Soybeans(N)	1998	28.3325	6.1780	27.7800	.4356
Soybeans(S)	1338	32.7754	9.2410	34.0861	(.0274)
Sorghum(N)	1512	55.5006	15.9962	54.4000	.3095
Sorghum(S)	456	47.7991	21.2240	47.4724	(.0474)

The standard errors of the correlation coefficients are in parentheses.

NASS mean yields were higher for 2 of the 4 crops. With respect to the median yield, the SOILS-5 data yielded higher median yields for 3 of the 4 crops. One possible reason that the SOILS-5 mean yields were not consistently higher than the NASS mean yields was that the optimal choice for a profit-maximizing farmer may have been to employ the "high" level of management practices assumed in the construction of the SOILS-5 estimates. Alternatively, the differences between the NASS and SOILS-5 data may simply reflect problems associated with the subjective nature of the SOILS-5 crop yield estimation process.

With respect to yield variability, the SOILS-5 data reflected higher standard deviations of mean yield than did the NASS data for all 4 crops. The correlations between the NASS and SOILS-5 mean yields range from .266 for corn to .563 for cotton.[23] Finally, the sample size is consistently lower for the SOILS-5 data, which indicates that actual production was undertaken in counties where SOILS-5 yield estimates were not reported. This result is somewhat surprising since the SOILS-5 estimates are provided for each mapping unit if the crop can be produced in an economically viable manner on the land, whether or not the crop was actually grown on the land.

In addition to using corn yield as a proxy measure for economic marginality, Heimlich (1989) calculated the mean net revenue per acre for a combination of eight major field crops as a proxy for economic marginality. The underlying assumption that Heimlich seemed to make in calculating his net revenue measure was that input prices and usage, output prices, and government policy parameters did not vary across space.[24] If this assumption

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[23] The correlation coefficients presented are the Fisher's Z transformation of Pearson correlation coefficients. We used this transformation to calculate standard errors that could be used to calculate confidence intervals.

[24] This assumption with respect to prices would hold if markets were fully integrated. Even if input prices are constant across regions, differences in soil quality make it unlikely that input use, and thus costs, are

did not hold, incorrect conclusions may be drawn when using net revenue as a measure of economic marginality. For example, assume crop yields are low on highly erodible land in two regions. This could lead one to conclude that economically marginal land, i.e., land with lower yields, is also environmentally marginal land, i.e., highly erodible land. If a net revenue measure were employed, a higher net revenue could be obtained in one region (even if crop yields were identical) if input usage (and thus costs) were lower in that region. This could lead one to conclude that more productive land, i.e., land generating higher net revenue, is also highly erodible land. Therefore the use of net revenue as a measure of economic marginality may generate results across space that are dependent only on differences in input use, prices, and policy parameters, not the inherent productivity of the land. If prices and the effects of government policy were site specific, the connection between land erodibility and net revenue would be more appealing theoretically. Since these variables are not site specific, this approach seems to abstract from the essential relationship between land erodibility and productivity. As a result, we did not employ net revenue as a measure of economic marginality in our study.

2.3.2 Measure of Environmental Marginality

To act as a proxy for environmental marginality in this study, we construct a soil erodibility index from the water and wind erodibility indices contained in the NRI data. The erodibility index EI is a numerical value that expresses the potential for a soil to erode by considering the properties of the soil (chemical and physical) and the climatic conditions where the soil is located. The EI does not take into account cropping or conservation management practices, so it measures the "inherent physical erodibility" of the soil. The higher the EI value, the more susceptible the soil is to erosion and the greater the investment needed to maintain production on the soil. A value of EI greater than 8 is the criteria that is employed by the USDA to denote a plot of land as being "highly erodible."

The erodibility index employed in this study is constructed as the sum of the numeric values associated with the wind and water erodibility indices.[25] The water-induced erodibility index is based on use of the RKLS components of the Universal Soil Loss Equation (USLE), where K is an inherent soil erodibility factor, R is a rainfall erosivity factor, L is

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constant across geographic areas.

[25] These indices account for factors that affect the erodibility of the land without regard to the usage or production practices employed on that land.

a slope-length factor, S is a slope-steepness factor. The K factor value for a particular soil type is determined from an equation that includes the following variables: silt percent, sand percent, organic matter content, structure (e.g., fine granular soil), and permeability . The K factor is assumed to be constant for each soil type, regardless of the production practices undertaken on the soil or the climatic differences associated with the geographic location of the soil. The rainfall erosivity factor R accounts for the soil erosivity associated with the impact of rain drops on the soil and the resulting runoff associated with the impact. It is a function of the kinetic energy associated with the rain drop impact and the maximum 30 minute intensity of the rainfall (Mitchell and Bubenzer 1980).

The RKLS measure expresses the level of sheet and rill erosion that would occur if the field were maintained in clean-tilled fallow (Lee and Goebel 1986). The index is adjusted (i.e., $RKLS/T$) to take into account the tolerance of the soil to maintain productivity in the presence of inherent soil erodibility. The T value is defined as the "the maximum rate of annual soil erosion that may occur and still permit a high level of crop productivity to be obtained economically and indefinitely" ((Lee and Goebel 1986), p. 42). Wind-induced soil erodibility is measured as $(C * I/T)$, where C measures the climatic components (e.g., windspeed and duration), I measures the susceptibility of the soil to wind erosion, and T measures soil tolerance. The I component is primarily a function of the surface cover and soil texture, including particle size (clods vs. fine granular) and ridge height and length, which is primarily a function of tillage practice.

In summation, we employ two measures of land productivity (mean crop yield and the coefficient of variation of mean crop yield) to proxy for economic marginality. The mean crop yield measure used in the site-specific research is the SOILS-5 estimated crop yield, while NASS county-level mean crop yield data were used in the aggregate portion of this study. Since the SOILS-5 data contain no measure of crop yield variability, the coefficient of variation of mean crop yield could be constructed only for the NASS data. We employ an erodibility index that incorporates the impact of water and wind on soil erodibility to proxy for environmental marginality. A list of variables and summary statistics for the site-specific data can be found in Table A.1, while a list of variables and summary statistics for the aggregate data can be found in Table A.2.[26]

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[26] The summary statistics for the squared climate variables and the temperature/precipitation interaction terms are not included in the tables.

2.3.3 Site-Specific Yield Model

Past research ((Kaufmann and Snell 1997), for example) has shown that any model attempting to explain crop yield should contain the following factors: management practices, climate, and soil characteristics.[27] Crop yield response models have typically been estimated in a single-equation framework with a linear model specification (Dixon, Hollinger, Garcia and Tirupattur 1994). Hansen (1991) concluded that "commonly estimated yield functions are linear across most inputs with quadratic or logarithmic measures of particular inputs with nonconstant marginal products." He tested alternative functional forms (logarithmic and translog) for corn and soybean crop yield equations and found that the linear model performed better. We use a linear specification of the crop yield equations in our study.

We use ordinary least squares (OLS) to estimate multiple regression equations with crop yield as the dependent variable and the aforementioned factors as regressors. While including rainfall, temperature, soil characteristics, and management practice variables in each equation, we estimate a separate equation for each of the crops in our study. The general form of the crop yield model is given by the following equation:

$$\begin{aligned} YLD_i = \quad & b_0 + b_1 \cdot TEMP + b_2 \cdot SQTEMP + b_3 \cdot PRECIP + b_4 \cdot SQPRECIP \\ & + b_5 \cdot TEMP * RAIN + b_6 \cdot EI + b_7 \cdot AWC + b_8 \cdot CFACT + \epsilon_i \end{aligned} \tag{2.1}$$

where YLD_i is the yield of crop i, $TEMP$ is the monthly mean temperature, $SQTEMP$ is the square of the monthly mean temperature, $PRECIP$ is the monthly mean precipitation, $SQPRECIP$ is the square of the monthly mean precipitation, $TEMP * RAIN$ is an interaction term between mean monthly temperature and precipitation, EI is the measure of soil erodibility, AWC is average water holding capacity, $CFACT$ is the cropping management factor, and ϵ_i is an error term.

Crop yields for soybeans, upland cotton, grain sorghum, and corn were used in this study. The yield data are the estimated yields contained in the SOILS-5 dataset. Even though crop yields were estimated for land defined as "noncultivated" cropland in the NRI if the soil could sustain production, we use data only from land defined as "cultivated cropland." This makes the comparison with the NASS county-level data more reasonable since actual yield data would have been collected only for land that was under cultivation.

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[27] Crop yield response models that employ time-series data should also include a variable to capture technological change. While technology adoption differs across space, the major impact occurs over time.

Since the SOILS-5 yields reported in 1992 (the data employed in this study) were estimated from data collected, when available, over the previous ten year period, we included all sites that were classified as "cultivated cropland" in either the 1987 or 1992 NRI. In the SOILS-5 data, crop yields were estimated for both irrigated and nonirrigated cropland. We ran regressions using both irrigated and nonirrigated crop yield data for this study, though only the results from the nonirrigated yields are presented.[28]

To capture the inherent productivity of the soil, we include the average water holding capacity (AWC). Average water holding capacity, the ability of the soil to store and supply water for plant use, is critical for plant development, particularly in areas that have limited and/or variable precipitation. The AWC was constructed from data contained in the SOILS-5 dataset. The maximum and minimum values for the variable are reported for individual soil layers. To construct measures that could be linked to the NRI site data, the minimum and maximum values of the AWC were averaged for each soil layer. The resulting mean value was then multiplied by the number of inches in that soil layer. The resulting product was then summed over all soil layers down to a predetermined soil depth. The resulting sum was then divided by the number of inches to the predetermined soil depth; therefore, the final value of the variable was reported per inch of soil. We used a soil depth of 30 inches in this study to construct our soil productivity measure.

Although the impact of weather variables on crop yield has generally been recognized (for example, see Runge (1968); Thompson (1969); and Teigen and Thomas Jr. (1995)), the complex interactions among weather, biological and chemical processes, and technological factors make it difficult to separate the crop yield impact of weather from those associated with the other variables (Metcalfe and Elkins 1980). Even with this limitation, the importance of including weather variables in any crop yield model can be demonstrated by noting that Teigen and Thomas found that over 90% of the variability of corn and soybean yields in the United States between 1950 and 1994 could be explained by variations in monthly temperature and rainfall.

While Kaufmann and Snell (1997) used rainfall and temperature data that corresponded to the phenological stages of crop development, they were looking at only one crop

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[28] The results were robust to the choice of irrigated or nonirrigated yield. We present the nonirrigated yield data to facilitate comparisons with the results found in Heimlich (1989). We include a variable, the percentage of nonirrigated cropland in the county, in the aggregate portion of our study to account for differences in nonirrigated and irrigated yields since we use total (irrigated and nonirrigated) yields from the NASS data. We chose to use total crop yield data since NASS fails to report irrigated and nonirrigated yields for a large number of counties.

(i.e., corn) and one geographic area (i.e., the Corn Belt).[29] The more typical approach is to include average temperature and rainfall measures over the growing season (e.g., Westenbarger and Frisvold (1995)) or include monthly measures of those variables for some or all months over the growing season (e.g., Dixon and Segerson (1999)). Ideally we would like to model climate variables in a manner that corresponds to the phenological stage of crop development rather than in a manner that corresponds to calendar designations, i.e., months. However, the scope of this study (i.e., the large geographic area and number of crops under study) and the limitation of available data prohibited a detailed modeling of the impact of climate variables on the phenological stages of crop development. To attempt to capture the impact of climate on crop yield, we include mean temperature ($TEMP$) and mean precipitation ($PRECIP$) for the critical months during the year. For the crops in our study, adequate precipitation and temperature in the months of May, June, July, and August are crucial for plant growth. Since the weather data is not site-specific, we assign the county averages to each NRI site within the county. Since crop yields have not been found to be a linear function of climate variables, a quadratic term was included for temperature ($SQTEMP$) and precipitation ($SQPRECIP$) to capture those nonlinear effects. A negative (positive) sign on the quadratic term would indicate a(n) diminishing (increasing) marginal impact of climate on crop yield. In addition, the impact of temperature on crop yield is highly dependent on the presence of rainfall (and vice versa). For example, the effect of above average temperatures may be mitigated with higher than average rainfall. We include an interaction term between the temperature and precipitation variables in each month to capture this effect.

While differences in input usage can account for differences in crop yield across space, data on chemical usage (expenditure) or capital intensity/technology adoption do not exist at the NRI site level. In an effort to capture the impact of these factors, we include a NRI variable, the C factor ($CFACT$), which is designed to capture the impact of cropping management practices.[30] Among other things, the C factor incorporates the impact of cover, cropping sequence, residue management, conservation tillage, growing season length, and cultural practices on crop production (Mitchell and Bubenzer 1980). The lower the

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[29] The phenological stages of crop development indicate the different stages of plant growth.

[30] The C factor is calculated as the ratio of soil loss from a specific combination of cropping practices to the soil loss associated with land in a tilled, continuous fallow condition. While the C factor directly addresses the impact of management practice on soil loss, its component factors also contribute to differences in yield. Given the lack of site-specific input and management practice data with respect to crop yield, the C factor provides a reasonable proxy measure.

C factor, the less soil loss that should occur from a given set of cropping management activities; therefore, a lower C factor would indicate the implementation of more intensive management practices with respect to the reduction in soil loss.[31] While these practices (e.g., conservation tillage) may enhance productivity in the long-run, it is likely that crop yields may decline in the short-term. Therefore, a higher C factor value may be associated with higher crop yields, at least in the short-run.

2.3.4 Aggregate Models

For the aggregate portion of the study, mean crop yields were constructed as ten-year (1983-1992) crop yield averages using NASS county-level yield data.[32] The site-specific variables contained in the NRI data were aggregated to the county level to correspond to the NASS data.[33] The NRI contains a weighting factor ($xfact$) that is equivalent to the number of acres that each NRI sample point represents. The $xfacts$ are summed for each county to give the total number of acres represented by the NRI sample points. The attribute value (e.g., C factor) is multiplied by the $xfact$, and then summed over all NRI sites within the county. Finally, the value obtained by summing the weighted attribute values was divided by the sum of the $xfacts$ for the county in which the sites reside to obtain a county average for the attribute in question. County averages of the soil erodibility measure EI ($AGEI$), C factor ($AGCFACT$), and average water holding capacity ($AGAWC$) were constructed in this manner. While the SOILS-5 data provided yields for irrigated and nonirrigated land, we constructed a variable ($PERNIRR$) for the aggregate portion of the study to capture the percentage of nonirrigated cropland within the county. All data from the NRI used to construct the county-level aggregate measures were limited to those sites associated with the cultivated cropland designation.

While differences in crop yield and yield variability across time and space are functions of input use and technological change, data limitations complicate their inclusion within our empirical framework. For example, crop-specific chemical usage or expenditure

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[31] The inclusion of the C factor and the erodibility index in our regression equations raises a potential issue of collinearity. One could expect that higher inherent soil erodibility would encourage farmers to undertake cropping practices, e.g., conservation tillage, to reduce potential soil loss. Pearson correlation coefficients that range from -.115 (SOILS-5) to -.140 (NASS) indicate that the inclusion of both variables does not pose a major problem.

[32] For each crop model, we used only those counties where the crop in question accounted for 10% or more of the total planted acres in the county.

[33] The temperature and precipitation data were already reported at the county level.

data are not available on the scale (i.e., county-level) employed in this study.[34] While technological change (e.g., precision farming and genetically engineered crops) has led to increases in crop yields over time, our focus is on differences in crop yield across space. As a result, differences in technology adoption across space are more relevant to our study. Though a body of research (see (Daberkow and McBride 1998); (Khanna, Epough and Hornbaker 1999); (Fernandez-Cornejo, Daberkow and McBride 2001); and (El-Osta and Mishra 2001)) have demonstrated a positive correlation between technology adoption and size of the farming operation (e.g., average number of acres comprising the farm), farm size could also represent a number of other influences, including economies of scale.[35] Finally, the rapid technological change of the 1990s occurred after our period of study. To avoid the lack of crop-specific chemical expenditure data and the difficulties associated with modeling technology adoption, we included the county average C factor ($AGCFACT$) to account for cropping management choices.

While crop yields are a proxy measure for economic marginality, the variation in crop yields may also play a significant role in the farmer's perception of the desirability of initiating or maintaining crop production on a particular plot of land. To account for this, we develop a measure of yield variability from the NASS time-series data. We construct the coefficient of variation of the ten-year average (1983-1992) of mean crop yields at the county level as our measure of yield variability. Many of the factors that contribute to crop yield should also contribute to yield variability. As a result, we include the same explanatory variables in the crop yield variability model as we did in the county-level crop yield model.

2.4 Data

This study makes use of data collected from a number of sources. In particular, we make extensive use of 1982, 1987, and 1992 NRI data (see chapter 1 for a general discussion of the NRI). Among other things, the measure of soil erodibility (EI) and the cropping management factor ($CFACT$) were contained in the NRI data. The soil productivity measure (AWC) was obtained from the Soil Survey Interpretations Record (SOILS-5) data.

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[34] An alternative model specification that included county-level total chemical expenditures was estimated. Given the lack of crop-specific expenditures, the results were difficult to interpret, and their inclusion did not change the relationship between crop yield (yield variability) and soil erodibility.

[35] An alternative model specification that included farm size was estimated, but the results were difficult to interpret. In addition, their inclusion did not change the relationship between crop yield (yield variability) and soil erodibility.

The estimated crop yields used in the site-specific portion of the study were also obtained from the SOILS-5 data, while the county-level mean crop yield data (and the constructed coefficient of variation data) were obtained from the NASS agency of the USDA.

In addition to the site-characteristic and yield data, our study required data on other variables that have an impact on crop yield. Monthly mean temperature and precipitation data were obtained from the PRISM database created from research undertaken by the USDA and Oregon State University. The data used in this study were 30 year (1961-1990) averages of precipitation and temperature for all counties in the United States (excluding counties in Alaska and Hawaii). The data on the measure of scale (i.e., average farm size in acres) was taken from the 1992 USDA Agricultural Census, while data on average chemical expenditures was constructed from 1987-1992 chemical expenditure data contained in the Regional Economic Information System (REIS) database from the Bureau of Economic Analysis (BEA). Data on these variables were collected at the county level.

2.5 Results

2.5.1 Acreage Distributions

The fact that cropland was not cultivated at a point in time indicates that the land was economically marginal at the existing input/output prices and government policy parameters. To determine if economically marginal land is also environmentally fragile, we can compare the measures of erodibility of cultivated and noncultivated cropland. If there is a positive relationship between economic marginality and environmental marginality, the erodibility measures should be higher on the noncultivated (i.e., economically marginal) cropland. We find a positive relationship in our data for the erodibility index in 1992, with the EI having a value of 12.623 on noncultivated cropland and a value of 7.028 on cultivated cropland.

The distribution of acreage across erodibility classes can also provide a clue as to the relationship between economic and environmental marginality. If a positive relationship exists, one would expect that noncultivated cropland (since it is economically marginal) would contain a higher proportion of land in the higher erodibility classes than would cultivated cropland. The results are displayed in Table 2.3. Within the cultivated cropland data, 74.2% of the acreage falls in the 3 classes associated with the lowest degree of soil

Table 2.3: Distribution of Cropland Acreage by Erodibility Class (1992)

Erodibility Classes	*Cropland*	
	Cultivated	Noncultivated
EI<2	20.6	20.5
2≤EI< 5	34.2	24.2
5≤EI< 8	19.4	15.9
8≤EI< 10	7.3	7.2
10≤EI< 15	9.0	11.7
EI≥ 15	9.5	20.5

erodibility, while the remaining 25.8% falls in the 3 classes of highest erodibility. Within the noncultivated cropland data, only 60.6% of the acreage falls in the lowest 3 erodibility classes, while the remaining 39.4% falls in the 3 highest classes. In particular, 20.5% of the acreage in noncultivated cropland falls in the class with the highest erodibility index value, while only 9.5% of the acreage in cultivated cropland exhibits the highest measure of erodibility. The results indicate that noncultivated cropland contains a higher percentage of more erodible soil than cultivated cropland, which gives some support to the conventional wisdom.

Table 2.4: Land Use Distribution Within Erodibility Classes (1992)

Erodibility Classes	*Land Use*		
	Cultivated	Noncultivated	CRP
EI<2	84.41	14.23	1.37
2≤EI< 5	87.00	9.40	3.60
5≤EI< 8	82.60	10.40	7.00
8≤EI< 10	79.16	9.81	11.03
10≤EI< 15	72.92	12.53	14.55
EI≥ 15	64.14	18.78	17.08

Alternatively, one could look at the distribution of land use within each erodibility class. Recall that the NRI erodibility index is only reported on land that is designated as cropland (cultivated or noncultivated) and land that is enrolled in the Conservation Reserve Program. The results in Table 2.4 indicate that the percentage of cultivated cropland generally decreases over the range of erodibility classes. As expected, the percentage of land enrolled in the CRP increases over the range of erodibility classes. While the changes in noncultivated cropland are not as dramatic as those in the CRP, land in the two highest erodibility classes contain a higher percentage of noncultivated cropland than do lower erodibility classes, except for the $EI < 2$ class. These results indicate that the percentage of cropland that is noncultivated or enrolled in CRP (as opposed to cultivated) increases as the level of soil erodibility increases. Again, this lends some support to the conventional wisdom that economically marginal land is associated with higher levels of soil erodibility.

2.5.2 Site-Specific Crop Yield Distributions

If economically marginal land is also highly erodible, we would expect to find a decrease in mean crop yields (and an increase in crop yield variability) as the level of soil erodibility increases. Table 2.5 presents data on the mean crop yield (and standard deviation of crop yield) across classes of the soil erodibility index. The erodibility classes were chosen to coincide with the categories employed by the NRCS in reporting their summary findings for the NRI. The highest estimated mean yield for each crop occurs on land where the erodibility index (EI) is less than 2, and the yields generally decline as the erodibility index takes on larger values. In addition, the standard deviation of mean crop yields tends to increase as the erodibility class increases.

Table 2.5: Site-Specific Mean Crop Yield by Erodibility Class (1992)

Crop	*Erodibility Classes*					
	$EI<2$	$2\leq EI<5$	$5\leq EI<8$	$8\leq EI<10$	$10\leq EI<15$	$EI\geq 15$
Cotton	649.559	638.379	478.161	435.233	439.357	433.237
	(135.568)	(175.926)	(189.460)	(181.219)	(195.095)	(211.240)
Corn	118.022	103.986	88.432	87.555	92.779	92.382
	(28.230)	(30.371)	(34.412)	(35.856)	(34.264)	(28.283)
Sorghum	75.803	67.462	50.831	43.729	40.481	38.149
	(17.224)	(16.378)	(17.282)	(16.973)	(19.043)	(21.191)
Soybeans	40.390	37.210	34.762	35.007	34.937	33.118
	(8.046)	(7.984)	(8.954)	(9.234)	(9.062)	(8.684)
C factor	0.270	0.253	0.244	0.242	0.248	0.223
	(0.106)	(0.096)	(0.100)	(0.105)	(0.121)	(0.128)

The standard deviations of mean crop yield and C Factor are in parentheses.

While the general trend supports the view that land productivity and soil erodibility are inversely related, crop yields do not decrease as erodibility levels increase for all of the crops. Mean crop yields for sorghum decline over the entire range of erodibility classes, but the results for soybeans, cotton, and corn are mixed. For example, mean corn yields decline for the 4 lowest erodibility classes, but the fifth class ($10\leq EI<15$) exhibits higher yields than land in the fourth class ($8\leq EI<10$). Even in cases where the yield generally declines over the range of erodibility classes, the magnitudes of the differences are quite small. For example, the soybean yield ranges from 35.007 to 33.118 over the four classes exhibiting the highest levels of erodibility. It should also be noted that the C Factor also generally declines over the range of erodibility classes. This indicates that more intensive cropping management practices with respect to the reduction in soil loss (for example, a higher percentage of land under conservation tillage) are conducted as the erodibility of the land increases. As previously discussed, a decline in the C factor may actually be expected to decrease crop yields in the short-run as cropping management practices are undertaken to reduce soil erosion.

2.5.3 Aggregate Crop Yield Distributions

Table 2.6 presents data on the mean crop yield (and standard deviation of crop yield) across classes of the soil erodibility index for the NASS data. In contrast to the findings for the SOILS-5 data, most of the crops do not exhibit their largest yields on land in the lowest erodibility class. Mean corn yields are highest in erodibility class 5 ($10 \leq \text{EI} < 15$), while soybean yields are highest in erodibility class 6 ($\text{EI} \geq 15$). In addition, the crop yields do not generally decline over the entire range of erodibility classes. For example, the lowest cotton yields occur in classes 3, 4, and 5, while the highest yields occur in classes 1, 2, and 6.

Table 2.6: Aggregate Mean Crop Yields by Erodibility Class (1992)

Crop	*Erodibility Classes*					
	$\text{EI}<2$	$2\leq \text{EI} < 5$	$5\leq \text{EI} < 8$	$5\leq \text{EI} < 8$	$10\leq \text{EI} < 15$	$\text{EI} \geq 15$
Cotton	599.666 (191.575)	593.667 (164.976)	482.803 (172.262)	430.329 (139.194)	447.485 (198.929)	584.364 (267.261)
Corn	86.869 (28.606)	91.874 (2.849)	89.173 (25.266)	93.283 (27.366)	93.347 (28.739)	92.382 (24.689)
Sorghum	55.725 (17.631)	56.129 (14.264)	56.145 (14.756)	55.998 (16.359)	54.070 (16.341)	53.762 (17.396)
Soybeans	25.722 (5.780)	28.671 (6.643)	27.630 (7.081)	28.566 (6.979)	28.869 (6.546)	29.331 (6.271)
C factor	0.256 (0.120)	0.254 (0.084)	0.229 (0.079)	0.228 (0.084)	0.235 (0.091)	0.218 (0.112)

The standard deviations of mean crop yield and C factor are in parentheses.

As in the SOILS-5 data case, the reduction in the C factor, and thus the implementation of more intensive cropping management practices with repsect to the reduction in soil loss, over the range of erodibility classes may actually reduce crop yields in the short-run, so the lack of a uniform decrease of crop yields over the erodibility classes may even be more pronounced if cropping management practices are excluded. Therefore, these results lend little support to the view that there is a close link between economic marginality (as measured by mean crop yield) and economic marginality (as measured by soil erodibility).

Table 2.7 presents data on the coefficient of of variation of mean crop yield (and standard deviation of the CV of crop yield) across classes of the soil erodibility index for the NASS data. A priori expectations are that the coefficients of variation would increase as the soil became more erodible if a positive link exists between economic and environmental marginality. Contrary to that expectation, the highest CV's generally occur in erodibility classes 3 ($5 \leq$ EI < 8) and 4 ($8 \leq$ EI < 10). In addition, there is no consistent pattern over the erodibility classes, though the CVs tend to increase over the first 3 to 4 classes and then decrease over the last 2 to 3 classes.

Table 2.7: CV of Crop Yields by Erodibility Class (1992)

Crop	*Erodibility Classes*					
	EI<2	$2 \leq$ EI < 5	$5 \leq$ EI < 8	$8 \leq$ EI < 10	$10 \leq$ EI < 15	EI ≥ 15
Cotton	22.763 (12.963)	23.852 (9.897)	27.681 (9.321)	28.330 (8.749)	27.885 (11.575)	25.724 (11.826)
Corn	20.440 (10.702)	21.359 (8.408)	22.579 (8.699)	22.667 (10.485)	23.331 (10.686)	21.457 (9.270)
Sorghum	19.336 (10.520)	20.220 (10.434)	21.028 (9.2870	20.632 (9.554)	20.872 (11.789)	18.390 (10.762)
Soybeans	16.909 (7.805)	18.903 (7.158)	21.005 (8.085)	20.648 (8.758)	20.146 (6.146)	19.467 (5.842)
C factor	0.256 (0.120)	0.254 (0.084)	0.229 (0.079)	0.228 (0.084)	0.235 (0.091)	0.218 (0.112)

The standard deviations of the coefficients of variation of mean crop yields and C Factor are in parentheses.

These results lend little support to the view that there exists a close link between economic marginality (as measured by the coefficient of variation of mean crop yield) and economic marginality (as measured by soil erodibility).

2.5.4 Site-Specific Crop Yields

The erodibility coefficient estimates, standard errors, and adjusted R-squares for the regressions using the mean estimated crop yields from the SOILS-5 data are presented in Table 2.8.[36] A negative coefficient on the erodibility index indicates that an increase in soil

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[36] Complete regression results for all of the models can be found in Tables A.3 through A.5.

erodibility (environmental marginality) leads to a decrease in crop yields, which indicates an increase in economic marginality. Therefore a negative sign on the erodibility coefficient implies a positive relationship between economic and environmental marginality.

The coefficients on the EI variable were negative for all of the crops in the study. In addition, the coefficient estimates were statistically significant at the 1% level for all of the crops. The adjusted R-squares ranged from .388 (soybeans) to .661 (sorghum), which indicates that the model has good explanatory power for cross-sectional data.

Table 2.8: OLS Results: SOILS-5 Crop Yields

Crop	*Erodibility Index*	
	Coefficient Estimates	Adjusted R^2
Cotton	**-4.596** (0.111)	.624
Corn	**-0.541** (0.008)	.547
Sorghum	**-0.582** (0.010)	.661
Soybeans	**-0.229** (0.003)	.388

The standard errors for the coefficient estimates are in parentheses.
The coefficient estimates in bold are significant at the α=.01 level.

The elasticities of the crop yields with respect to the erodibility index were inelastic in all cases. The elasticities ranged from -.041 for corn to -.087 for sorghum.[37] Given these elasticities, an increase in the soil erodibility index from its mean value of 7.79 (near the 70th percentile) to the value at the 80th percentile (10.6), a 36% increase, would result in decreases in yield ranging from 1.48% for corn to 3.13% for sorghum. If the soil erodibility index increased to the value at the 90th percentile (16.4), a 111% increase, crop yield reductions would range from 4.55% for corn to 9.66% for sorghum, respectively. The regression results for the SOILS-5 data provide support for the belief that there is a positive relationship between economic and environmental marginality.

Land productivity, as proxied by the average water holding capacity (AWC), should be positively related to crop yield since the ability of the soil to retain and transport water is essential for plant growth. As expected, the coefficient on AWC was positive and statistically significant in all cases. The C factor ($CFACT$) variable captures the impact

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[37] All of the elasticities in this study were calculated at the mean values of the erodibility index and crop yields.

of cropping management practices on soil loss (and indirectly crop yield). Since a lower C factor indicates more intensive cropping management activities designed to reduce soil loss, a priori expectations were that a higher value for the C factor would be associated with higher crop yields. As expected, the coefficient on $CFACT$ was significant and positive in all cases. Since the C factor incorporates management activities designed to mitigate potential soil loss, this positive relationship may indicate that these cropping management activities, such as cover and crop rotation, lead to reductions in short-term yield in an effort to protect the long-term productivity of the land.

Finally, the coefficients on the temperature, precipitation, squared terms of those variables, and interaction terms were of mixed sign and statistical significance. No discernible pattern exists across crops with respect to the climate variables, though higher precipitation in August is associated with higher crop yields in all cases. There was also a high degree of collinearity (as expected a priori) between all of the climate variables, which made the estimates of the standard errors and t-statistics unreliable. Since these variables were not the focal point of the study, all of the temperature, precipitation, squared terms, an interaction terms were retained in the estimating equations. The same problems existed with respect to the climate variables in both of the aggregate models.

2.5.5 Aggregate Crop Yields

The erodibility coefficient estimates, standard errors, and adjusted R-squares for the regressions using the mean estimated crop yields from the NASS data are presented in Table 2.9.[38] Again a negative coefficient on the erodibility measure would indicate support for the belief that there is a positive relationship between economic and environmental marginality. Consistent with the findings with the SOILS-5 data, the coefficient signs are negative in all cases, with only the coefficient in the cotton yield equation being insignificant at the 10% level.

The elasticities of the crop yields with respect to the erodibility index were inelastic, ranging from -.013 for corn to -0.062 for sorghum. The magnitudes of the elasticities would indicate that changes in the level of soil erodibility would have a slightly smaller impact on crop yields than was evidenced in the SOILS-5 case. An increase in the erodibility index from the mean value of 8.48 (near the 60th percentile) to the value at the 80th

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[38] Complete regression results for all of the models can be found in Tables A.7 through A.9.

Table 2.9: OLS Results: NASS Crop Yield

Crop	*Erodibility Index*	
	Coefficient Estimates	Adjusted R^2
Cotton	-0.292 (1.095)	.778
Corn	**-0.142** (0.052)	.622
Sorghum	**-0.407** (0.165)	.549
Soybeans	**-0.057** (0.017)	.815

The standard errors of the coefficient estimates are in parentheses.
The coefficient estimates in bold are significant at the α=.10 level.

percentile (12.30), a 45% increase, would result in yield decreases of between .23% (cotton) to 2.79% (sorghum). Even an increase to the 90th percentile (16.38), a 93% increase in the erodibility index, would result in decreases in yield ranging from .47% for cotton to 5.77% for sorghum. In both the SOILS-5 and NASS cases, an increase in the soil erodibility index would have a more pronounced impact on sorghum yields than it would for the yields of the other crops. The adjusted R-squares ranged from .549 (sorghum) to .815 (soybeans), which indicates that the models have good explanatory power for cross-sectional data. The regression results using the NASS yield data provides evidence to corroborate the findings in the site-specific portion of the study. Both support the conventional wisdom that there is a strong, positive relationship between economic and environmental marginality.

As expected, the percentage of nonirrigated cropland ($PERNIRR$) exhibited a statistically significant negative relationship with all mean crop yields. As with the SOILS-5 data, the coefficient on average water holding capacity ($AGAWC$) was positive, though it was not significant in the cotton and sorghum yield equations. The coefficient estimates on county-level average C factor ($AGCFACT$) were positive for corn and cotton, though negative for soybeans and sorghum. The soybean and sorghum results were inconsistent with those contained in the site-specific portion of the study. As with the results from the SOILS-5 data, the coefficients on the temperature, precipitation, squared and interaction terms are of mixed sign and statistical significance. The results varied by crop within each sample (SOILS-5 or NASS). For example, increases in May rainfall are associated with decreases in corn and sorghum yields and increases in cotton and soybean yields using the SOILS-5 data. In addition, the results are not consistent for each crop across samples.

For example, increases in precipitation in May are associated with lower corn yields in the SOILS-5 data and with higher corn yields in the NASS data. Again it should be noted that these variables are highly collinear and that separating out the individual effects may be impossible.

2.5.6 Crop Yield Variability

The erodibility coefficient estimates, standard errors, and adjusted R-squares for the regressions using the coefficients of variation of mean crop yields from the NASS data are presented in Table 2.10.[39] A positive sign on the coefficient on the erodibility index indicates that an increase in soil erodibility (environmental marginality) increases crop yield variability. If the uncertainty associated with increases in yield variability leads farmers to view this land as economically marginal, a positive sign on the erodibility index implies a positive relationship between economic and environmental marginality. Even though crop yield variability is a measure of economic marginality, it is not clear that higher crop yield variability is associated with higher soil erodibility. It may be the case that increases in soil erodibility simply decrease mean yields without altering the variability of yields. Therefore the relationship between crop yield variability and soil erodibility is primarily an empirical question.

The estimated coefficients on the erodibility index ($AGEI$) had positive signs in all 4 crop equations, but are statistically insignificant at the 10% level in 3 of the 4 cases. Even in the statistically significant case (soybeans), the elasticity of the coefficient of variation of soybean yields is of a very small magnitude (.022). The adjusted R-squares ranged from .305 (sorghum) to .482 (cotton). The explanatory power of the crop yield variability models are considerably less than that of the mean crop yield models.[40]

As would be expected, a higher average water holding capacity ($AGAWC$) is associated with lower crop yield variability. All of the coefficient signs are negative and significant. Counties with soils that have higher average water holding capacities are less dependent on consistent rainfall, and are thus less likely to experience high yield variability. The percentage of nonirrigated cropland ($PERNIRR$) exhibited a statistically significant positive relationship with crop yield variability in all cases. This was expected since the lack

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[39] Complete regression results for all of the crops can be found in Tables A.11 through A.13.

[40] This result is likely a function of the lack of data concerning climate variation. While mean precipitation and temperature data explain much of the variation in mean crop yield, it is the variation in those variables that help explain variations in crop yield.

Table 2.10: OLS Results: CV Crop Yield

Crop	*Erodibility Index*	
	Coefficient Estimates	Adjusted R^2
Cotton	0.006 (0.068)	.482
Corn	0.032 (0.026)	.327
Sorghum	-0.082 (0.122)	.305
Soybeans	**0.052** (0.031)	.389

The standard errors of the coefficient estimates are in parentheses.
The coefficient estimates in bold are significant at the α=.10 level.

of irrigation would have a dramatic impact on crop yield during months with below average precipitation, but would have less of an impact during months of average or above average precipitation. The coefficients on the C factor ($AGCFACT$) are statistically insignificant at the 10% level in all cases. As with the results from the SOILS-5 and NASS mean yield data, the coefficients on the temperature, precipitation, squared and interaction terms are of mixed sign and statistical significance.

2.6 Conclusions

Conventional wisdom has long held that economically marginal land is also environmentally marginal (i.e., fragile). Very little research has been conducted to test this belief, with the few studies that have been conducted yielding mixed results. To test this relationship, we use site-specific (SOILS-5) and county-level (NASS) data on measures on economic marginality (crop yield and yield variability) and environmental marginality (the NRI soil erodibility index).

We employ two methodological approaches in our study. First, we analyze the distribution of our productivity measures across different levels of erodibility. The mean crop yields (SOILS-5 and NASS) generally diminished as the level of erodibility increased, though higher yields were often found in classes exhibiting higher levels of erodibility. While the coefficient of variation of mean crop yields generally increased as the level of erodibility increased, low yield CV's were also found at high levels of soil erodibility. These results are somewhat consistent with Heimlich's findings that mean yield and soil erodibility are weakly associated, though the general trend of diminishing (increasing) mean yields (yield variability) as levels of soil erodibility increase provide some support to those espousing the conventional wisdom.

Second, we conduct a more detailed analysis by regressing our measures of economic marginality (mean yield and the coefficient of variation of yield) on the erodibility index and a set of conditioning variables. This analysis yields consistent results in support of the conventional wisdom that economically marginal land is also likely to be environmentally fragile, at least with respect to increasing levels of soil erodibility. Although the estimated coefficients were negative and significant, the elasticities were generally small, though increases in the erodibility index from the mean value to values at the 80th and 90th percentile of the index distribution resulted in reductions in yields that ranged from .5% to 5.8% in the SOILS-5 data. With respect to yield variability, our results indicate that there is a very weak (and mostly insignificant) relationship between yield variability and soil erodibility. As previously discussed, it may be the case that increases in soil erodibility reduce mean yields while having little or no impact on yield variability.

Our results do not confirm Heimlich's general conclusion that there is a weak relationship between economic marginality (crop productivity) and environmental marginality (soil erodibility). While the crop yield distribution results provided only weak support for the conventional wisdom, our regression results indicate that there appears to be a significant negative relationship between mean crop yield and soil erodibility. This would support the assertion that there is a positive association between economic and environmental marginality. This raises concerns that government policies that encourage production on economically marginal land (i.e., land with low mean crop yields) may lead to increases in soil erosion as more erodible soil is brought into production. As a result, it is important to consider the impact of government income support and risk management policies on acreage allocation decisions.

Chapter 3

Impact of Crop Insurance on Acreage Response and Input Usage: The Case of Upland Cotton

3.1 Introduction

Recent research has been conducted to test the impact of federally-subsidized crop insurance on the production decisions of farmers. Specifically, a growing body of research has centered on the inducement that crop insurance provides for farmers to produce on economically marginal land. In this context, economically marginal land (i.e., the "extensive margin") refers to acreage not currently under production that would be brought into production by increasing the return or decreasing the risk (yield variability) associated with production on that land. This "extensive margin" of production involves altering production decisions on two levels. First, production could be encouraged on land within a growing region where production would not otherwise be undertaken without the increases in return or reductions in risk provided by crop insurance. At the same time, the availability of crop insurance may induce production of a crop in regions where the crop would not otherwise be produced due to less suitable growing conditions.

These potential production inducements may be exacerbated by the provision of premium rate subsidies designed to encourage producer participation in the crop insurance program. Subsidy payments are calculated as a percentage of premium payments, which are constructed to reflect the risk associated with the production of the insured crop. As a result, increases in premium rates associated with the acceptance of more risk are partially offset by increases in premium rate subsidies. This has the potential to encourage the production of more risky crops on more risky land since the government is partially offsetting an actuarially-fair premium rate.

If the inducements to alter production patterns are large, the resulting distortions may have negative impacts on related markets, the environment, and the likelihood of obtaining the goals of other government policies. For instance, insurance-induced increases in production may reduce the price of the commodity. This would partially offset the impact of other government program payments designed to stabilize farm income variability. These changes may also have an impact on factor input markets as fertilizer and pesticide use is altered in response to increases in production, changes in crop mix, and reductions in production risk. The change in input use in response to reductions in risk provided by the availability of crop insurance is known as the "intensive margin" impact. If the provision of insurance causes farmers to reduce input usage below prescribed levels, this "moral hazard" problem may increase the likelihood that the farmer will receive indemnity payments. Finally, if the economically marginal land is also environmentally fragile, crop insurance-induced production changes may lead to changes in soil erosion and environmental externalities, such as water quality degradation.[1]

Recent research has provided contradictory results as to the impact of the provision of crop insurance on crop acreage allocation. Keeton et al. (2000) and Griffin (1996) found substantial acreage increases due to the availability of federally-subsidized crop insurance, while Young, Schnepf, Skees and Lin (2001b) and Goodwin et al. (2004) found relatively small production increases due to insurance availability. Research has also provided contradictory results as to the impact of crop insurance on chemical/fertilizer use. Goodwin (1993), Babcock and Hennessy (1996), and Goodwin et al. (2004) found that fertilizer/chemical use decreases with the purchase of crop insurance, while Horowitz and Lichtenberg (1994) found that farms that purchase more crop insurance tend to use more chemicals and fertilizers. The extensive and intensive impacts of federally-subsidized crop insurance continue to remain an open empirical question.

In terms of crops that have been studied, much of the work has concentrated on corn, soybeans, wheat, and barley. While these crops make up a large percentage of total U.S. agricultural production, concerns have been raised as to the potential impact

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[1] Possible decreases in fertilizer and chemical use in response to the provision of crop insurance (i.e., the moral hazard concern) may actually lead to an improvement in environmental amenities.

of subsidized crop insurance on planting decisions made with respect to upland cotton. Upland cotton is grown in most of the states in the southern half of the U.S., from Virginia to California. Questions have been raised, particularly with regard to plantings in northwestern Texas, about the viability of production without the availability of crop insurance. The average loss ratio on a national basis for cotton between 1980 and 1998 was 2.55 (Makki 2002).[2] This means that farmers received indemnity payments of $2.55 for every dollar paid in premium payments. Recent research (Young et al. (1991); Young, Vandeveer and Schnepf (2001a)) indicates that cotton production also tends to be more responsive to changes in crop insurance premium rate subsidies than other crops, with the possible exception of wheat. Young et al. (2001b) also note that per unit premium subsidies for upland cotton vary substantially across geographic location, ranging from $0.01 per pound in the Far West to $0.12 per pound in the Southern Plains during the period from 1995 to 1998. As a result, production incentives may vary across regions.

In this study, we attempt to address a few of these issues in the crop insurance literature. As previously mentioned, upland cotton has received limited attention in the literature although questions have frequently been raised concerning the presence of possible crop insurance-induced production distortions. Grain sorghum, though an important crop in some areas (e.g., the Prairie Gateway region), has received little attention in the crop insurance and acreage response literature. Furthermore, most recent studies have looked at the impact of crop insurance on production decisions either at the national level or in a limited geographic area. For example, Keeton et al. (2000) used Crop Reporting District (CRD) data from across the U.S., while Wu (1999) used farm-level data from one state (Nebraska). Young et al. (2001b) accounted for differences across regions in a simulation model, while Goodwin et al. (2004) looked at two USDA farm resource regions (Heartland and Northern Great Plains). There is scant research in areas where most of the concerns have been raised (i.e., the Prairie Gateway region) and areas that saw major shifts in cotton production (i.e., the Southern Seaboard and Mississippi Portal regions) during the 1990s. In addition, the wide geographic area represented by these regions will allow us to better explore the impact of land quality differences on production decisions.

This study is organized in the following manner. Section 2 provides a brief dis-

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[2] Loss ratios are constructed by dividing the indemnity payments by the producer-paid portion of the premium payments. Excluding cotton, the loss ratios ranged from 1.33 for corn to 2.49 for peanuts during this period.

cussion of the characteristics of upland cotton production. Section 3 provides a review of the relevant literature. In particular, we present a discussion of the literature concerning the demand for crop insurance and the impact of crop insurance on the intensive and extensive margins. Section 4 presents the methodology employed in this study. We discuss the economic model, the estimation process, and the data in this section. A presentation and discussion of the results is provided in section 5. A summation of the findings and concluding remarks are presented in the final section.

3.2 Cotton: Background

Upland cotton (i.e., *Gossypium hirsutum*) is primarily grown in the United States in an area that stretches from Virginia to California along the southern tier of states. Upland cotton production occurs in most states across this region, though the chief producer is Texas which produces 31% of the upland cotton grown in the United States. Mississippi, California, Georgia, and Arkansas all produce between 9% and 11% of the upland cotton grown in the United States (USDA-NASS). Cotton production varies by USDA farm resource region. Figure 3.1 provides a map of the farm resource regions. A third of all cotton farms are located in the Prairie Gateway region, 14% are in the Fruitful Rim region, 24% are in in the Mississippi Portal region, and 24% are in the Southern Seaboard region. In terms of production quantities, 26% of all cotton produced within the U.S. is produced in the Fruitful Rim region, 25% in the Mississippi Portal region, 24% in the Prairie Gateway region, and 20% in the Southern Seaboard region (Brooks 2001).

The average growing season temperature on the northern border of the growing region is 77 degrees Farenheit, which seems to be the minimum temperature necessary for profitable commercial cotton growth. The length of the growing season along the northern border is approximately 180-200 days, and average rainfall is 30-60 inches. The best soils for upland cotton growth are the loams of the Mississippi Delta and southwestern regions. Optimal soils should be well-drained, moderately fertile, and contain high organic matter content. While the optimal pH levels should be between 5.8 and 6.5, upland cotton can grow on soils with a wide range of pH levels. Upland cotton growth is dependent on adequate moisture during the spring and summer, adequate sunlight, and a long frost-free growing season (Metcalfe and Elkins 1980). The growing season in the United States generally runs

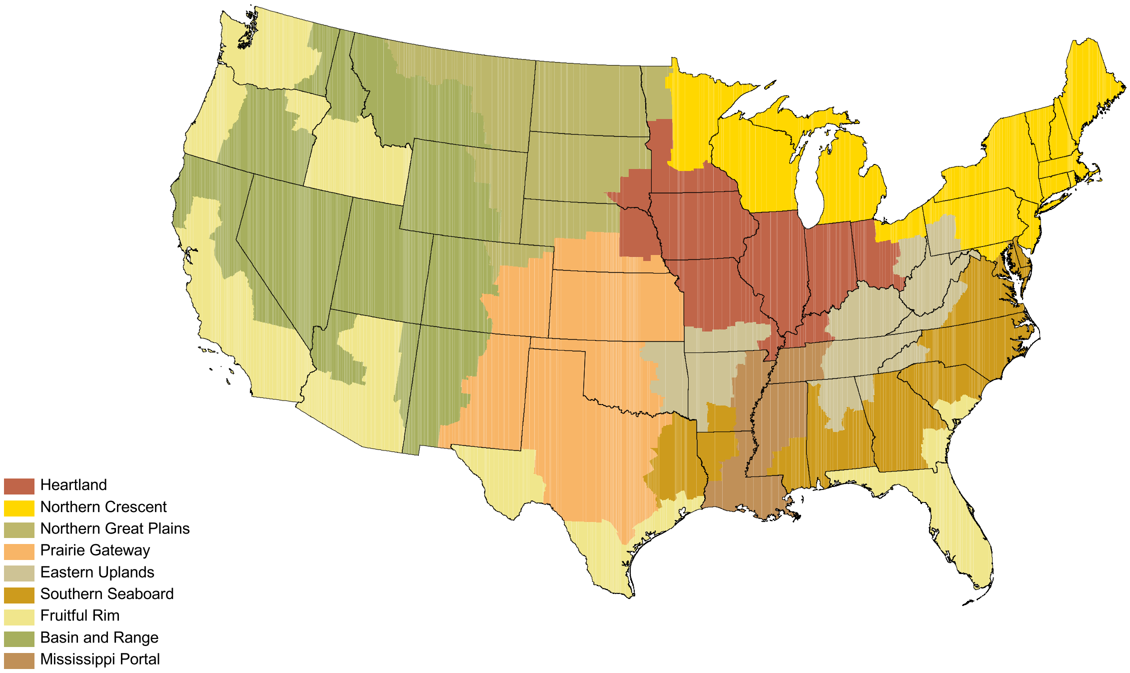

Figure 3.1: USDA Farm Resource Regions

from April to November. Growers in the Fruitful Rim region generally plant in April, while growers in the other farm resource regions generally plant during May. Most growers in the Heartland, Fruitful Rim, and Mississippi Portal regions harvest in October, while growers in the Prairie Gateway and Southern Seaboard generally harvest in November (Brooks 2001).

3.3 Literature

Since the 1980s, a major research emphasis has been placed on determining the impact of agricultural policies on farming production decisions, including input usage, crop mix choices, and planted acreage. Recent research has been conducted to determine the impact of federally-subsidized crop insurance and disaster relief payments on those production decisions. In particular, focus has centered on: (1) the determinants of insurance participation, (2) the impact of insurance participation on acreage allocation decisions, and

(3) the impact of these allocation decisions on input use. In this section, we will concentrate on outlining the relevant literature in each of these three areas.

3.3.1 Demand for Crop Insurance

Extensive research has been conducted to determine the factors that affect the decision to purchase crop insurance. Econometric studies of insurance participation have occurred at both the aggregate level (see Goodwin (1993), for example) and the farm level (see Goodwin and Kastens (1993); Coble, Knight, Pope and Williams (1996)). In most of these studies, insurance participation has been shown to be positively related to the expected net return to the purchase of insurance. The expected net return to insurance participation is determined by premium rates, federally provided subsidy payments, and expected indemnity payments. Specifically, participation rates should be positively correlated with expected indemnity payments and federally provided subsidies and negatively correlated with premium rates. In addition, the following explanatory variables have often been included in crop insurance demand equations: farm size or wealth, farm diversification, crop yield variability, producer education and experience, and the history or expectation of subsidy or disaster relief payments.

The expected rate of return to crop insurance has been included in most crop insurance demand studies. Two general approaches have been employed to account for the expected return. Some studies (Gardner and Kramer (1986); Coble et al. (1996)) have constructed a specific return variable that incorporated expected indemnity payments and premium rates, while other studies (Smith and Baquet (1996); Goodwin (1993)) included expected indemnity payments and premium rates as separate explanatory variables. Gardner and Kramer defined the expected rate of return as the ratio of the expected indemnity payment minus the insurance premium to the insurance premium. They found a positive relationship between this variable and the demand for crop insurance. Using Kansas farm-level data, Coble et al. (1996) also found a positive relationship between the expected return to insurance and the level of participation. In addition, they included the variance of the return to crop insurance and found a significantly negative relationship between the return variance and crop insurance purchases.

Premium rates have been included in crop insurance demand equations in a number of studies (Goodwin (1993); Barnett, Skees and Hourigan (1990); Goodwin et al. (2004)).

Using county-level data, Barnett et al. (1990) found a negative relationship between premium rates and insurance participation. They estimated elasticities of demand with respect to the premium rate of between -0.18 and -0.23 for various model specifications (Knight and Coble 1997). Goodwin (1993) also had similar findings. He estimated elasticities of demand that ranged from -0.32 to -0.73 for participation rates and coverage level measures of insurance demand, respectively.[3] Both studies indicated that the demand for crop insurance is relatively inelastic with respect to changes in the premium rate. Goodwin (1993) also included an interaction term between premium rates and loss ratios to examine whether the premium response was conditional on the loss ratio.[4] He found that the price elasticity of demand decreased as the loss ratio increased, i.e., the farmer was less responsive to increases in the premium rate if the expected indemnity payment was higher.

In a comprehensive study of crop insurance demand, acreage response, and input use for corn/soybeans in the Heartland region and wheat/barley in the Northern Great Plains region, Goodwin et al. (2004) found that insurance participation was negatively related to premium rates for 3 of the 4 crops under study. The expected indemnity payment (i.e., the historical average loss ratio) was positive and significant in all crop insurance participation models. Consistent with the results contained in Goodwin (1993), the premium rate-loss ratio interaction term exhibited the same relationship to crop insurance demand for 3 of the 4 crops in the study. Analyzing corn crop insurance demand in Indiana with a discrete choice ranked logit model, Vandeveer and Loehman (1994) included variables to capture the premium rate, the indemnity price, and the probability of payment. The coefficients on these variables were of the expected signs, but only the probability of receiving a payment was significant at the 5% level.

While most studies included some variable to proxy for the cost or expected return from insurance (with Black and Dorfman (2000); Wu (1999) as exceptions), most studies do not make an explicit distinction between the decision to purchase crop insurance and the subsequent choice of a coverage level. Smith and Baquet (1996) used a Heckman two-stage estimation process to analyze the insurance participation and coverage-level decisions separately. In addition, they computed the expected returns to the purchase of crop insurance and divided their sample into those with negative and those with positive expected returns.

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[3] Insurance participation was measured as acres insured divided by total acres, while coverage level was measured by insurance liability per planted acre.

[4] The loss ratio for a given year was calculated as the average of the county's ten year loss ratio divided by the state loss ratio for that year.

In the full sample, the premium rate variable was negative in both the participation and coverage-level equations, but was significant only in the coverage-level equation. In the model of farmers with negative expected returns to crop insurance, the premium rate variable was positive but insignificant for both participation and coverage-level decisions, while the premium rate variable was negative (as in the full sample case) in the model of farmers with positive expected insurance returns. Their results indicate that premium rate changes may have an impact on the choice of coverage levels, though they may have little impact on the purchase decision.

In addition to the expected return to insurance, a number of studies have included some form of yield variability to capture the production risk facing the farmer. One would expect that the demand for insurance would be positively correlated with yield variability since higher yield variability would increase the likelihood of receiving indemnity payments. This expected positive relationship was found in Smith and Baquet (1996); Wu (1999); and Goodwin et al. (2004). Coble et al. (1996) included a variable to capture the variance of expected revenue (i.e., the square of the market price times the variance of yield) which captured the yield variability. They also found that farmers were more likely to purchase crop insurance if they were facing higher expected yield variability. Using Montana wheat farmer survey data, Smith and Baquet (1996) included variables to capture expectations about yield variability (i.e., a scale variable representing the importance of yield variability in the insurance purchase decision) and actual yield variability (i.e., the standard deviation of historical yields). They found that the subjective view of yield variability was positively related to insurance purchases, while the coefficient on the standard deviation of yield was positive but insignificant.

Since the purchase of crop insurance is undertaken to reduce the adverse effects of yield (and thus revenue) shortfalls, the demand for crop insurance should also be dependent on the availability of other risk management tools. Variables used to proxy for risk management options include the following: farm size, farm diversification, off-farm labor, debt/asset ratios, and land value. When using farm-level survey or Agricultural Risk Management Survey (ARMS) data, studies also include education and experience data which may impact the farmer's knowledge and use of various risk management tools.[5] Using Geor-

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[5] The ARMS is a stratified, probability-weighted survey of U.S. farms that is conducted on an annual basis. Among other things, the ARMS collects data on farm financial conditions, operator characteristics, and production practices.

gia farm-level survey data, Black and Dorfman (2000) found that age and education was negatively correlated with crop insurance purchases, while the experience level of the farmer was positively correlated. Smith and Baquet (1996) found that age and experience were not significant in insurance purchase decisions for Montana wheat farmers, while the level of education exhibited a positive relationship to insurance purchases. Wu (1999) found a significant positive coefficient on farming experience, but an insignificant positive coefficient on education. Given the conflicting results and scarcity of farm-level survey data, we can't draw any definitive conclusions concerning the impact of these variables on crop insurance purchase decisions.

Farm diversification measures are typically included in many studies (Black and Dorfman (2000); Vandeveer and Loehman (1994); Coble et al. (1996); Goodwin (1993); and Goodwin et al. (2004)) to proxy for alternative risk management tools available to the farmer. The a priori belief is that farming operations that are more diversified are insulated against yield shortfalls; therefore, a higher level of diversification should be correlated with a lower demand for crop insurance. Alternatively, higher levels of diversification could occur due to higher levels of farmer education and experience. If those variables are correlated with higher levels of insurance demand, farm diversification may be positively correlated with higher insurance purchases. Farm diversification has generally been measured by a Herfindahl index of crop diversification (Vandeveer and Loehman (1994)); Coble et al. (1996)) or by the percentage of total farm sales derived from livestock sales (Goodwin (1993); Goodwin et al. (2004)).[6] In Goodwin's 1993 study, the percentage of farm sales from livestock sales was not significantly related to crop insurance demand. The same measure was found to be was positively related to corn and soybean insurance participation, but negatively related to barley and wheat insurance participation in Goodwin et al. (2004). The Herfindahl index was negatively (though not significantly) related to insurance purchases in the Coble et al. (1996) study, but positively (and significantly) related in the Vandeveer and Loehman (1994) study. Using the number of crop/livestock enterprises as a proxy for diversification, Black and Dorfman (2000) found a negative and significant relationship with crop insurance demand for cotton and peanuts. These mixed results do not support any a priori belief concerning the relationship between farm diversification and crop insurance

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[6] The percentage of total sales generated from livestock sales has been employed as a measure of diversification since the revenue generated from livestock sales is not generally dependent on the same factors that affect yield shortfalls. Therefore farmers who generate a larger percentage of their income from livestock sales are insulated against revenue shortfalls due to crop yield shortfalls.

purchases, and thus it remains an open empirical question.

Farm net worth or value of farm sales exhibited a significant negative relationship to insurance purchases in a number of studies (Coble et al. (1996); Black and Dorfman (2000)); and Wu (1999)). Studies (Vandeveer and Loehman (1994); Black and Dorfman (2000)) including a measure of farm debt, e.g., debt to asset ratios, demonstrate a positive relationship between farm debt and insurance purchases. The negative relationship between net farm worth and insurance purchases can be explained as an indication of the farmer's ability to self-insure, while the positive relationship with farm debt may indicate the existence of insurance participation requirements imposed by lending institutions. Barnett et al. (1990) argued that farm size should have a positive impact on crop insurance purchases since larger farms generate larger insurance commissions and therefore encourage more aggressive sales efforts. In addition, they argue that there is a delivery-cost advantage to selling to larger farms due to the high fixed administrative costs associated with insurance delivery. This expected positive relationship was found by Goodwin (1993), Black and Dorfman (2000), and Vandeveer and Loehman (1994). Vandeveer and Loehman (1994) found that off-farm income was negatively related to insurance purchases, while Wu (1999) found a positive relationship. The Wu results were statistically insignificant, while the Vandeveer and Loehman results were statistically significant.

Since the availability of government payments, such as ad hoc disaster payments, insulates the farmer against yield and revenue shortfalls, the demand for crop insurance should be inversely related to the provision of other government payments. Some studies have attempted to include actual or expected government payments in the crop insurance demand equations. Wu (1999) found a significant positive relationship between the purchase of corn insurance and participation in other government programs. Vandeveer and Loehman (1994) found that the demand for crop insurance exhibited a negative and significant relationship with the farmer's expectation that they would continue to receive disaster relief payments. Just and Calvin (1990) found that farmers who receive disaster payments are more likely to insure, while Goodwin and Kastens (1993) found that farmers who do not expect to receive disaster payments are more likely to insure. Smith and Baquet (1996) included a dummy variable to represent whether or not the farmer had received disaster relief payments within the last five years. This variable exhibited a statistically significant positive relationship with the decision to purchase crop insurance, but was insignificant in the coverage-level decision.

Few studies have conditioned the purchase of crop insurance on differences in land quality. Since higher quality land should be positively correlated with higher expected yield and lower yield variability, we could expect a negative relationship between land quality and crop insurance purchases. One could also argue that the higher expected yield on high quality land would increase insurance purchases since the value of any lost production would be larger. Wu (1999) included a measure of soil erosion and soil quality variables in a probit model of corn insurance participation. He found that the soil quality variables (i.e., soil clay percentage, organic matter content, and available water capacity) were not significantly correlated with insurance purchases, but a measure of soil erosion (i.e., a variable incorporating soil loss from water and wind erosion) was positively and significantly (at the 1% level) related to insurance purchases. Goodwin et al. (2004) included a variable (i.e., the percentage of county acres in the USDA land capability classes 1 and 2) to proxy for the quality of land. They found a positive and significant relationship between higher quality land and the demand for crop insurance in 3 of the 4 crops under study.

3.3.2 Extensive Margin

The impact of crop insurance on the "extensive" margin has also been extensively researched during the last fifteen years. Concerns about the potential impact of crop insurance on acreage allocation decisions has increased over the last decade since insurance participation rates have increased in response to higher premium subsidy payments. This literature falls within the more general framework of the acreage allocation (response) literature, particularly that portion of the literature that explores the impact of government programs on acreage and crop mix decisions. While an extensive literature exists concerning the development of acreage response models (Nerlove (1956); Houck and Ryan (1972); Chavas, Pope and Kao (1983); Shumway (1983); and Chavas and Holt (1990)), the emphasis in this study is on the impact of government programs, particularly federally-subsidized crop insurance, on the farmer's acreage allocation decisions. As a result, we present a brief discussion of the literature addressing the development of acreage response models in the presence of government programs, then we extend the discussion to acreage response in the presence of crop insurance.

There have been two basic approaches employed in the literature to account for the impact of government agricultural policies on the farmer's land allocation choices. One approach (see Morzuch, Weaver and Helmberger (1980), for example) is to disaggregate the sample by time periods where similar policy regimes existed and run separate regressions for each group of years. Policy variable parameters such as loan deficiency payments, acreage diversion rates, and base acreage requirements are often included in the estimation equations to model government policy. In contrast to the explicit modeling of the policy variables, annual dummy variables (see Goodwin et al. (2004)) or policy dummy variables (see Shideed and White (1989); Duffy, Shalishali and Kinnucan (1994)) have been employed within this framework. This approach may create a serious empirical estimation problem by reducing the available degrees of freedom unless pooled cross-sectional, time-series data are used. Another concern is that this approach may not be feasible if the government programs or policy parameters are of short duration (Duffy, Richardson and Wohlgenant 1987). While this disaggregated approach may account for differences across policy regimes, the development of government policy variables within each policy regime is still very difficult since the program provisions are often complex.

The alternative approach (see Houck and Ryan (1972), for example) is to incorporate the impact of farm program provisions into a “supply-inducing price.” To account for the impact of government programs, an “effective support price” is constructed to include the target or other announced support price and any restrictions placed on acreage allocation.[7] The supply-inducing price is then constructed from the effective support price and the expected market price. Some researchers used the higher of the expected market price and the effective support price to proxy for the supply-inducing price (Shumway (1983)), while others have used some combination of the two prices to proxy for the supply-inducing price (Bailey and Womack (1985); Duffy et al. (1987)). Duffy et al. (1987) pointed out that the use of an “either-or” approach ignores the fact that government price supports provide a guaranteed lower bound on income that would affect the production decisions of a risk-averse producer even in cases where the expected market price exceeded the effective support price. Within the supply-inducing price framework, other variables, such as diversion payments, have also been included in the estimating equations to capture the impact of government policies.

Regardless of the approach taken, the acreage response models generally have included a variable measuring expected price or expected return (i.e., revenue or profit). A

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[7] See Duffy et al. (1987) for a good overview of the alternative methods and issues involved in constructing a supply-inducing price.

number of approaches have been employed to generate price expectations. These included naive expectations represented by lagged historical cash prices (Chembezi and Womack (1992)), futures prices (Morzuch et al. (1980)), and a combination of cash and futures prices (Chavas et al. (1983)). In a study of alternative forms of price expectation formation in agricultural supply analysis, Shideed and White (1989) concluded that there was no universally superior method to form price expectations. If an expected market return variable was included, the researcher also needed to generate expected yields. Most studies employed some form of lagged yield as a proxy for expected yield. Davison and Crowder (1991) used the average of actual yield over the preceding three years, Chavas and Holt (1990) regressed actual yield on a trend variable, and Duffy et al. (1994) regressed actual yield on lagged yield and a trend variable.

Most studies found differences in acreage response as agricultural policies and policy parameters changed. In the studies that employed the disaggregated approach (e.g., Morzuch et al. (1980)), significant differences were found in acreage response between program and non-program years. For example, Lee and Helmberger (1985) rejected the null hypothesis of coefficient stability between "free market" and "farm program" years at a 1% level of significance. They found that acreage response was more own-price responsive in program years, and hypothesized that this finding was due to the land use alternatives (e.g., land diversion) provided by the government programs. Similar results were found in McIntosh and Shideed (1989). While both studies found higher own-price elasticities for corn in program years, the results for soybeans were less conclusive. Within the "supply-inducing price" approach, expected price variables which included some weighting for support prices (e.g., Houck and Ryan (1972); Duffy et al. (1987)) exhibited a positive significant relationship with crop acreage allocations. Models which contained land diversion payment rates or acreage allotment restrictions as explanatory variables found that acreage allocation was negatively related to those variables. Among other attempts to include government program variables in the acreage response literature, Wu and Brorsen (1995) and Wu and Segerson (1995) included ARP rates, expected prices of alternative crops (including target prices for program crops) and corn target prices in their corn acreage response equations.[8] They found that these variables were generally significant in the crop acreage response equations

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[8] The Acreage Reduction Program (ARP) required farmers to idle a certain percentage (ranging from 5% to 35%) of their base acreage to maintain eligibility for deficiency payments. The ARP rates varied by crop and acted as a tool of supply management so that acreage could be reduced in periods of high commodity stocks (and thus low market prices) for a particular crop.

that they estimated.

The research into the impact of government programs on acreage response has been extended during the 1990s to include the impact of crop insurance. In an early attempt to explore this issue, Gardner and Kramer (1986) looked at the impact of disaster relief payments on acreage response. Disaster relief payments could be viewed as crop insurance without premium payments, though the impact on planting decisions may not be equivalent to crop insurance since there is no guarantee that disaster relief payments will be received when the planting decisions are made. They compared changes in cropland acres harvested between 1974 and 1978 in counties with crop insurance and those without crop insurance. Counties without crop insurance were those that exhibited high yield variability and were excluded from the program due to concerns over the actuarial soundness of the program.[9]. They found a larger expansion of cropland in counties where crop insurance was not available. Since cropland in those counties exhibited higher yield variability (i.e., risk), Gardner and Kramer argued that the provision of crop insurance in those counties, proxied by the disaster payments program, with higher yield variability would encourage cropland expansion to a greater extent than would occur on lower risk (i.e., crop insurance eligible) land.

Griffin (1996) studied the impact of crop insurance and disaster payments on the acreage allocated to wheat production and pasture in the Great Plains region in the 1978-1992 period. Using county-level, time-series data, he estimated an OLS model that regressed wheat acreage as a share of wheat and pasture acreage on a number of explanatory variables, including the returns to wheat and pasture, disaster payments, crop insurance, and the deficiency payments available for wheat during this time period. He found a statistically significant positive relationship between wheat acreage and crop insurance participation, where insurance participation was measured as the ratio of crop insurance liability to market revenue at the county level. A significant positive relationship also existed between wheat acreage and disaster payments as proxied by the ratio of total crop insurance premiums to total crop insurance liability at the county level. Wheat set-aside rates (i.e., the required percentage of wheat acreage diverted from production to be eligible to receive deficiency payments) and Conservation Reserve Program (CRP) acreage exhibited a signif-

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[9] The expansion in the availability of crop insurance across crops and geographic regions did not occur until the 1980s when the federal government attempted to replace ad hoc disaster relief payments with crop insurance as a means to protect farmers against adverse yield and revenue shocks (Vandeveer and Young 2001)

icant negative relationship with wheat acreage.[10] He estimated that the existence of crop insurance and disaster payments shifted approximately 2.29 million acres from pasture to wheat production.

He also estimated a model that compared low subsidy (1974-1977) and high subsidy (1989-1992) periods for six major crops in the region. The change in a county's acres planted to six major crops as a percent of the county's planted acre capacity, i.e., a measure of cropping intensity, was used as the dependent variable. He regressed this variable on a number of regressors, including crop insurance participation, disaster payments, deficiency payments, and CRP acreage. Similar to the findings from the previous model, crop insurance participation and disaster payments increased cropping intensity. Statistically significant coefficients were estimated for all of the explanatory variables except deficiency payments. He estimated that 16 million additional acres were brought into production between the two periods due to expansions in the government programs. This expansion offset many of the gains (10 million acres taken out of production) made in the retirement of environmentally fragile land due to the CRP.

Keeton et al. (2000) employed a similar approach to study the effect of disaster assistance and crop insurance programs on the acreage planted for six major crops in the United States. They used data on crop acreage by CRD (Crop Reporting District) for 285 CRD's during two time periods - 1978-1982, a low support period, and 1988-1992, a high support period. They again used an OLS approach to regress the change in total cropland use within the CRD between the two periods on a set of explanatory variables. The explanatory variables used included the change in expected revenue, the change in insurance rate premiums paid by farmers, the change in net crop insurance subsidies per dollar of revenue, and the change in crop insurance participation. They also included a variable (change in base acres) to capture the impact of deficiency payments that were available during this period, but for which data could not be obtained.[11]

They found a statistically significant positive relationship between changes in cropland use and changes in crop insurance transfers, crop insurance participation, and com-

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[10] The Conservation Reserve Program was enacted in 1985 as a tool to remove "highly erodible" land from production. The government provided rental payments and shared in the costs of planting cover vegetation or other land changes designed to reduce soil erosion.

[11] A historical base acreage in a particular crop is required for the farmer to be eligible to receive deficiency payments. The farmer is paid the the difference between the target price and the market price on a per unit basis. The total payment is this difference, if the target price is higher than the market price, times the base acreage multiplied by the average historical yield associated with the farm. The deficiency payment program was eliminated in the FAIR Act of 1996.

modity base acres. They found a significant negative relationship between changes in cropland use and changes in crop insurance premium rates. Disaster payments were found to be marginally significant.[12] They concluded that the provision of these risk management programs induced farmers to increase production on economically marginal land. They estimated that 1.5 million acres of cropland are brought into production for every one percentage point increase in crop insurance participation. With a 30% increase in crop insurance participation since 1980, this implies that approximately 45 million acres of economically marginal land were converted into cropland use.[13]

Young et al. (2001b) used county level data on crop acreage and crop insurance subsidies to model the impact of subsidy changes on acreage allocation for eight crops in seven U.S. agricultural regions. They created "price wedges" by converting premium subsidies, delivery cost reimbursements, and underwriting losses and gains into per unit production subsidies for each crop in each region. They took the average of the production subsidies during the 1994-1998 period, and then divided by the average production of the crop in each region to get per unit subsidies. They then used the USDA's POLYSYS-ERS simulation model to simulate acreage response with and without the subsidies. They estimated an increase of 600,000 acres (0.2% of total U.S. acres in production), but noted that more substantial increases occurred among specific crops and regions. In particular, they simulated a 1.2% increase in cotton acreage in the presence of premium subsidies. Using a similar approach, Vandeveer and Young (2001) looked at the effect of federal crop insurance subsidies on wheat acreage in the period subsequent to the 1996 farm legislation. In contrast to a base case of unsubsidized crop insurance, they found that total wheat acreage was roughly 0.5% higher (i.e., an increase of 300,000 to 350,000 acres) in the case where crop insurance was subsidized. Considering the impact on seven competing crops, they found that total acreage in the eight crops would increase by 900,000 acres. While changes in wheat and total acreage varied by geographic region, the impacts were small in magnitude.

Using Nebraska farm-level data, Wu (1999) employed a simultaneous equations approach by estimating equations for corn insurance participation and crop shares for corn, soybeans, hay, and pasture. Corn insurance participation was included as an explanatory

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[12] This could partially be explained by the fact that the delivery of disaster payments is uncertain, and therefore not an important factor in the decision to determine acreage and crop mix.

[13] Cropland use includes land in crop production, land in CRP, and land that has been idled due to other acreage reduction programs sponsored by the federal government.

variable in the crop share equations. The purchase of crop insurance was positively correlated with increases in acreage in corn, soybeans, and hay, while negatively related to pasture acreage. The results were only significant in the soybean share equation. In addition, he included interaction terms between crop insurance participation and total farm acreage, the number of cattle, and number of off-farm work days in each of the four crop share equations.[14] Coefficients on ten of the twelve interaction terms were significant (though of mixed signs) in the crop share equations; therefore, Wu concluded that the purchase of crop insurance affected land allocation choices. For example, farmers who owned more cattle would allocate a smaller portion of their land to hay and pasture if they had purchased corn insurance.

Unlike many other studies in the acreage response literature, Wu (1999) included a series of variables capturing land characteristics - clay percentage, organic matter percentage, land slope, and available water capacity - in the crop share equations. While only six of the sixteen coefficient estimates were significant at the 10% level, the signs were generally consistent with expectations based on agronomic theory. The impact of corn insurance participation on crop mix was also estimated for different farm sizes. Farms of all sizes were more likely to allocate land to corn and soybean production and less likely to allocate land to hay and pasture if they purchased corn insurance. With the purchase of corn insurance, farmers also increased the share of total acreage planted in corn and soybeans, while decreasing the share of land allocated to hay and pasture. The shifts toward corn production (and away from hay and pasture) became smaller in magnitude as farm size increased.

Using data from the Heartland and the Northern Great Plains regions, Goodwin et al. (2004) estimated a system of equations representing farmer decision variables, i.e. insurance participation, crop acreage response, and input use.[15] This approach contrasted with previous research that failed to take into account the simultaneous nature of the decision process and, therefore, did not account for the endogenous nature of some of the independent variables.[16] They found a statistically significant acreage response for corn and soybean production to changes in insurance participation. The response was small in

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[14] The last two variables were included as proxy measures for farm diversification.

[15] The Heartland and Northern Great Plains are two of nine regions enumerated in "Farm Resource Regions" (2000). The Heartland region represents the primary corn growing areas in the U.S., while the Northern Great Plains region represents the primary areas of wheat and barley production.

[16] Smith and Goodwin (1996) and Wu (1999) used Wu-Hausman tests to demonstrate that insurance, crop mix, and chemical use decisions are not exogenous and can best be estimated using a simultaneous equations approach.

magnitude with elasticities of acreage response to increases in insurance participation of 0.010 to 0.003 for corn and soybeans, respectively. They found an acreage elasticity with respect to insurance participation of 0.005 for wheat and 0.048 for barley.

While their results indicated that increased participation in insurance programs provoked a statistically significant acreage response in 2 of the 4 crops, this response was, however, relatively modest. Conducting simulations using those acreage elasticities, they found that across-the-board decreases of 30% in insurance premiums significantly increased participation but result in acreage increases of about 0.28% for corn and 0.059% for soybeans. While the increase in wheat acreage was modest (0.12%), the response in barley acreage was somewhat higher (1.02%). In addition to the impact of crop insurance purchases, they found that the impact of land characteristics (land capability class, T-factor, and K-factor) on acreage response varied by crop and resource region. In the same vein, CRP enrollment was associated with significant decreases in crop acreage for soybeans and corn, though exhibited no significant impact on wheat and barley acreage.

3.3.3 Intensive Margin

The impact of crop insurance on the "intensive" margin has also been extensively researched during the last twenty years. The intensive margin refers to changes in chemical (i.e., pesticide and fertilizer) application rates as a result of the provision of crop insurance. Potential moral hazard problems exist if farmers reduce chemical use below prescribed levels due to the reduction in production risk associated with the provision of insurance. Early explorations of this question concentrated on defining the risk properties of pesticides and fertilizers. Pope and Kramer (1979) explored the impact of production risk on input use. Using a stochastic production function (incorporating yield variability) and a CRRA utility function, they found that a risk-averse agent would use more (less) of an input which marginally decreases (increases) risk in the single-input case. They concluded that the results were ambiguous in the two-input case.

Loehman and Nelson (1992) extended the Pope and Kramer work to include multiple inputs. They categorized inputs as either risk increasing or risk decreasing and risk substitutes or risk complements. " If the inputs (or pairs of inputs) are risk substitutes and both are risk increasing (reducing) individually, then the use of at least one and maybe both inputs will decrease (increase) with increasing risk aversion. If the use of only one input decreases, then use of the other one will increase. On the other hand, if one input is risk reducing and the other is risk increasing, then with increasing risk aversion the use of the risk-reducing input should increase and the use of the risk-increasing input should decrease. If the inputs are risk complements and both are risk-increasing (reducing), then the use of both should decrease (increase) with increasing risk aversion" (Soule et al., p.6). The Loehman-Nelson results indicated that the impact of risk management tools (e.g., crop insurance) on input use depends on both the risk properties of the input and the degree of risk aversion exhibited by the farmer.

Addressing the impact of crop insurance on input use, Ahsan, Ali and Kurian (1982) demonstrated that crop insurance encourages agents to increase the use of risk-increasing inputs in a one-input, one-output model. In the same vein, Nelson and Loehman (1987) also showed that farmers would demonstrate risk neutrality in input choices in the presence of actuarially-fair crop insurance. Both results assume full coverage and the absence of moral hazard. Quiggin (1992) developed conditions under which crop insurance would lead to a decrease in input use in the presence of moral hazard. He assumed two states of nature (good and bad) where the marginal product of the input is greater in the "good" state. He also assumed that the contract is not contingent on input use. He concluded that the provision of crop insurance would reduce input use for both risk-reducing inputs and those inputs that do not affect risk, while increasing input use for those inputs that are "strongly risk-increasing." [17] The impact was ambiguous for inputs that were classified as "weakly risk-increasing." The basic conclusion that could be drawn from this body of theoretical work was that the impact of crop insurance on input use was primarily an empirical question.

Horowitz and Lichtenberg (1994) argued that pesticides and fertilizers may actually be risk-increasing inputs, contrary to popular belief. They argued that an input is risk-increasing if it adds relatively more output to "good" states than "bad" states, therefore increasing the difference between the output in the two states. In bad states, the marginal product of the pesticide or fertilizer may be low or even negative. For example, poor growing conditions may lead to small insect populations, so the marginal product of a pesticide applied in that case will be very low. On the contrary, good growing conditions may lead to higher pest infestations, and therefore higher pesticide productivity. Fertilizer

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[17] An example of a "strongly risk-increasing" input is an input where the marginal product is negative in a bad state of nature, such as fertilizer.

usage may have the same effect since they tend to be productive when rainfall is high, but detrimental (they tend to burn dry soil) when rainfall is low. Thus pesticide and fertilizer use tends to increase output in good states and decrease output in bad states.

Noting that the availability of crop insurance tends to decrease the yield uncertainty facing the farmer, Horowitz and Lichtenberg argue that this encourages farmers to take more risk. The traditional thinking would lead one to believe that this should lead to a decrease in input use since the inputs are assumed to be risk-reducing (the moral hazard problem). Horowitz and Lichtenberg pointed out that the moral hazard problem could lead to an increase in input use if they are viewed as risk-increasing. In other words, the reduction in risk associated with the provision of crop insurance could act as a substitute for the risk reduction provided by fertilizer and pesticide use. Using farm-level data from the 1987 Farm Costs and Return Survey, they concluded that chemical usage increased with increases in crop insurance purchases. For example, they found that those purchasing crop insurance applied 19% more nitrogen per acre, spent 21% more on pesticides, and increased insecticide treatment by 63%.

Smith and Goodwin (1996) criticized the findings of Horowitz and Lichtenberg by pointing out that an input that increased the variance of yields would also tend to increase the expected (mean) yield. While an increase in yield variance tends to increase the probability of receiving an indemnity payment, an increase in expected (mean) yield will lower the probability. Smith and Goodwin argued that increases in input use were unlikely to increase indemnity payments for two reasons. First, the yield that triggers an indemnity payment is based on a 10 year average of the farm crop yield. If higher input use increases actual yield (and thus raises the 10 year average yield), the trigger yield will also increase, resulting in a lower probability of receiving an indemnity payment. Second, increases in input use raise production costs and lower the gains that could be obtained from any increases in indemnity payments.

Smith and Goodwin also argued that the methodology employed by Horowitz and Lichtenberg was flawed. Horowitz and Lichtenberg used a recursive estimation system based on the belief that insurance purchase decisions were made before the input application decision. Smith and Goodwin argued that the decisions should be treated as simultaneously determined.[18] Failure to use a simultaneous systems approach would lead to a positive bias

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[18] They conducted Wu-Hausman tests which indicated that the input application and insurance purchase decisions were not exogenous decisions.

in the crop insurance coefficient which would imply that the availability of crop insurance encourages farmers to apply more chemical inputs. Using data from Kansas wheat farming practices in the 1990-91 period, they found that an increase in insurance participation decreased the farmer's expenditures on chemical inputs. Their results indicated that insured farms spent \$4.23 per acre less on chemical inputs (fertilizers, herbicides, and pesticides) than noninsured farms. They also included chemical expenditures as a regressor in the insurance participation equation and found that farmers with higher chemical expenditures were less likely to purchase crop insurance.

Babcock and Hennessy (1996) also criticized the findings of Horowitz and Lichtenberg on the grounds that their underlying assumptions, not just methodology, were flawed. Horowitz and Lichtenberg assumed that pesticide and fertilizer application could theoretically lead to lower yields. Using farm-level data from Iowa farms growing corn in the period between 1986 and 1991, they found that fertilizer use, as measured by pounds per acre, significantly decreased the probability of low yields. They did not look at pesticide applications. Horowitz and Lichtenberg also assumed that farmers were risk averse. Using a CARA utility function, Babcock and Hennessy tested for different levels of risk aversion, and found that increased insurance purchases induces less fertilizer use at most levels of risk aversion. Again, they did not look at pesticide applications.

Wu (1999) conducted Wu-Hausman tests on farm-level data from Nebraska and found that he could reject that the input application and insurance purchase decisions were exogenous. This confirmed the findings of Smith and Goodwin, and gave additional credence to the criticism of the approach employed by Horowitz and Lichtenberg. While criticizing the recursive estimation procedure, he found that changes in the crop mix may make the overall relationship between insurance participation and fertilizer and chemical usage less clear. If crop insurance encouraged farmers to bring additional land into production, input use could increase with insurance participation. In addition, he argued that if insurance encourages shifting toward crops with more demanding input requirements, insurance participation may actually increase fertilizer usage. Thus, the expected relationship between insurance participation and input usage is unclear.

Goodwin et al. (2004) estimated a system of equations where chemical expenditures were included as an explanatory variable in the crop insurance demand equation and crop insurance participation was included as an explanatory variable in the input demand equations. They found that fertilizer and chemical expenditures exhibited the expected negative effect for all of the crops in the study. In particular, higher chemical expenditures implied lower insurance purchases in the insurance participation equation and higher insurance participation implied lower fertilizer and chemical expenditures in the input demand equation. Goodwin, Vandeveer, and Deal used county-level aggregate chemical expenditure data. Since the expenditure data were not crop-specific, it would be difficult to disentangle the moral hazard and acreage/crop mix dimensions of the changes in input use.

Using farm-level data collected on wheat farming in seventeen states in the 1998 Agricultural and Risk Management Study (ARMS), Nimon and Mishra (2001) were able to disaggregate fertilizer and pesticide expenditures. They used a two-stage OLS-Probit model to estimate equations for input use and insurance participation. In addition, they modeled the new revenue insurance instruments instead of the traditional yield based instruments.[19] They found that the combined pesticide and fertilizer expenditure variable showed a negative relationship with insurance participation. This confirmed the findings of Smith and Goodwin. After disaggregating fertilizer and chemical expenditures, they found that crop insurance purchases exhibited a strong negative impact on fertilizer expenditures, while they exhibited a small positive impact on pesticide expenditures. Since fertilizer expenditures were considerably larger than pesticide expenditures in wheat production, they argued that this explained the negative sign on the combined expenditure variable. Their results partially reconciled the findings of Horowitz and Lichtenberg and Smith and Goodwin. At the least, they confirmed the possibility that pesticides and fertilizers may exhibit different risk properties.

The empirical investigations (Smith and Goodwin; Horowitz and Lichtenberg; Goodwin, Vandeveer, and Deal; Wu and Babcock; and Nimon and Mishra) of the impact of crop insurance on input use contained estimating equations for chemical use or expenditures. In addition to measures of crop insurance participation, these equations included other potential determinants of input use such as crop acreage, measures of land productivity and erodibility, precipitation, expected crop yield, and crop yield variability. In addition to crop insurance purchases, Smith and Goodwin (1996) found that total farm acreage and the proportion of acreage devoted to the crops in the study (i.e., corn, soybeans, and milo) were positively correlated to chemical expenditures. Goodwin et al. (2004) found a neg-

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[19] Goodwin et al. (2004) also looked at the impact of the new revenue insurance instruments. They found that the availability of revenue insurance did not change the negative relationship between insurance participation and chemical and fertilizer expenditures.

ative relationship between chemical expenditures and land capability class and a positive relationship between crop acreage and chemical expenditures for 3 of the 4 crops in their study. In their examination of midwest corn farmer's input use decisions, Horowitz and Lichtenberg (1993) employed a more extensive range of input measures including nitrogen per acre, potassium per acre, insecticide acre-treatments, and pesticide expenditures per acre. The significance of their regressors (corn yield, corn yield CV, precipitation, percentage of acres in alternative uses, and a number of operator characteristics) varied by input measure. None of the regressors were significant across the range of input measures.[20] In their study of the impact of alternative management practices on acreage allocation, input use, and soil erosion, Wu and Babcock (1998) included a number of soil quality variables in their phosphorous and nitrogen fertilizer use estimating equations. They did not find any consistent statistical relationship between soil quality characteristics and input use.

3.3.4 Summary

In conclusion, there seems to be substantial agreement on the factors that may contribute to crop insurance purchase decisions. In particular, the expected return to insurance purchases exhibits a positive correlation with insurance purchases, with premium rates exhibiting a negative correlation and expected indemnity payments exhibiting a positive correlation. In addition to expected return variables, theory and empirical evidence indicate that any crop insurance demand equation should include, at a minimum, the following variables: a measure of farm diversification, a measure of yield variability, a measure of land quality, a measure of farm size, and a measure of alternative government payments. While individual farmer characteristics contribute to the insurance purchase decision, the lack of available farm-level data precludes the inclusion of individual farmer characteristics, though often relevant, into the estimating equations.

The impact of crop insurance purchases on acreage allocation and crop mix is still an unresolved issue. Some studies (e.g., Goodwin et al. (2004)) have found a significant though small impact on acreage allocation, while other studies (e.g., Keeton et al. (2000)) have found that the provision of crop insurance may have a substantial impact on farmer's acreage allocation decisions. Evidence has also been provided in a number of studies that

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[20] The coefficient of variation (CV) of yield is the standard deviation of the yield divided by mean yield. Unlike the standard deviation or variance, the CV takes into account differences in scale (e.g., mean).

the impact may vary by crop and geographic location. Given the lack of farm-level data, gathering additional evidence from different crops and geographical locations would help clarify the mixed results using county-level data. If county-level data is to be used, researchers (for example, Wu (1999) and Goodwin (1993)) have found that a simultaneous equation systems approach is more appropriate than the OLS approach in modeling farm production decisions.

Finally, the impact of crop insurance on input use (the moral hazard problem) is still unresolved. The theoretical literature indicates that there is a complex relationship between crop insurance and input use that depends on both the risk properties of the input and the degree of risk aversion exhibited by the farmer. Results from the empirical literature are also mixed and frequently limited to specific crops and geographic areas. Some studies (Horowitz and Lichtenberg (1993)) found a positive relationship between crop insurance and input use, while other studies (Smith and Goodwin (1996) found a negative relationship. In addition, little evidence exists concerning the significance of the other determinants of input use. While total crop or farm acreage measures tend to exhibit a positive relationship with input use, the statistical significance of other variables vary by crop and geographic location. Finally, Nimon and Mishra (2001) point out that crop insurance may have differential impacts on pesticide and fertilizer use. While their findings may explain some of the contradictions in other studies, the lack of disaggregated input usage or expenditure data makes additional research difficult.

3.4 Methodology

3.4.1 Introduction

In our study, we model a two-crop farm enterprise. The insurance choice (i.e., the participation decision) is made jointly with other production decisions that must be made by producers.[21] The farmer faces a number of decisions at the time of planting. He must decide what to produce, how much acreage to allocate to the production, how to produce the commodity (i.e., input use), whether or not to participate in a number of available agricultural programs provided by the government, and whether or not to

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[21] See Shumway, Pope and Nash (1984) for a discussion of joint production decisions on allocatable land.

undertake additional private risk management activities (i.e., hedging). In this study, we focus on the acreage allocation, input use, and government program participation decisions. Although we model the impact of other agricultural programs, we focus our attention on the federal crop insurance program. As a result, we estimate a system of equations that embody the multi-product nature of the farming enterprise and the joint nature of the production decisions.

While our focus is on the impact of crop insurance on acreage and input use decisions, the insurance participation decision is made within the context of the farmer's participation in other agricultural programs provided by the federal government. As outlined in section 1.1, our study period was characterized by two basic policy regimes embodied in the Food, Agriculture, Conservation, and Trade Act of 1990 (FACT) and the Federal Agricultural Improvement and Reform Act of 1996 (FAIR). The FACT Act continued government price supports and planting flexibility limitations, while the FAIR Act eliminated target price-based support payments and limitations on planting flexibility.[22] As a result of the differences in agricultural policies embodied in these two different regimes, we estimate our model for two distinct periods : 1990-1995 and 1996-2000.

Cotton production occurs in four primary USDA farm regions, though we restrict our analysis to three of those regions - Southern Seaboard, Mississippi Portal, and Prairie Gateway. In addition, we combine the Southern Seaboard and Mississippi Portal regions into one region since they are relatively homogeneous with respect to crop mix.[23] This will limit our study to 2 regions - Prairie Gateway and Southern Seaboard/Mississippi Portal - and therefore simplify our analysis and the presentation of our results. We estimate crop insurance demand and acreage response equations for two crops in each region. Cotton, the focal point of this study, is treated as one of the crops in both regions.[24] On the national level, the primary competing crops for cotton are corn, soybeans, wheat, and grain sorghum (Lin et al. 2000). Since they are generally considered to be the major competing crops in the respective regions, we include soybeans in our model for the Southern Seaboard/Mississippi

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[22] The FAIR Act maintained the commodity loan program. Under this program, farmers could still receive benefits through marketing loan gains if they received a loan or through loan deficiency payments even if they did not take out a commodity loan. See section 1.1 for a discussion of the commodity loan program.

[23] We account for differences between regions by including a dummy variable for the Southern Seaboard region.

[24] We also estimated models for each crop combination - cotton/soybeans and cotton/sorghum - that covered the entire 10 year period and all counties where the planted acreage of each crop comprised at least 10% of total crop acreage in the county. We employed annual and regional dummy variables to account for differences across space and time. The results from this specification did not alter our major conclusions.

Portal region and grain sorghum in the Prairie Gateway region.[25] In addition to our 4 equations (i.e., a crop insurance demand and acreage response equation for each crop), an equation is included to model the determinants of chemical expenditures. Therefore, our analysis of crop acreage response and insurance participation decisions in the two regions in our study leads to a system of five equations for each region - acreage response equations for the two crops, insurance participation equations for the two crops, and an equation representing input usage.

3.4.2 Model

Extensive research has been conducted to determine the factors that affect the decision to purchase crop insurance. The demand for crop insurance, (i.e., crop insurance participation) has generally been modeled using two measures of participation. One approach has used the ratio of insured acres to total planted acres as the dependent variable in the insurance participation equation. Goodwin (1993) has argued that this approach does not account for changes in coverage levels that may occur even if the number of acres insured does not change. For example, an increase in premium subsidy rates for larger coverage levels may induce farmers to increase coverage levels on existing covered acres. The acreage approach would not indicate an increase in insurance participation. Goodwin et al. (2004) suggested that the ratio of actual insurance liability to maximum potential liability should be used as the measure of insurance participation. In the above example, this approach would take into account the increase in coverage level (and thus insurance participation). Actual liability is measured by the real liability purchased by the farmer. Following Goodwin, Vandeveer, and Deal, we construct an approximate measure of total possible liability by taking the product of the futures market price, planted acres, and 75 percent of the county average yield for the preceding ten years.[26] The premium rate is constructed by subtracting subsidy payments from total premium payments, then dividing by total liability. Therefore, the premium rate reflects the producer-paid premium per dollar of liability purchased. It should be noted that the insurance program data are available only for those farms that actually purchase insurance. Therefore, our premium rates may

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[25] In addition to the inclusion of cotton and soybeans (grain sorghum), a 3 crop model was estimated for each region that included equations for corn insurance demand and acreage response. While the results did vary slightly in the 3 crop model, the added complexity did not change our major conclusions.

[26] The 75 percent coverage level was the maximum of the coverage level choices afforded most farmers during this period.

understate the actual rates faced by the entire insurance pool if nonbuyers face higher rates. This criticism is also relevant for most other empirical studies of insurance demand.

Extensive research (see Gardner and Kramer (1986) and Barnett et al. (1990), for example) indicates that the demand for insurance (i.e, insurance program participation) should be positively related to the expected return to insurance. Expected returns are a function of both premium rates and expected indemnity payments. There is also evidence that agents exhibit a differential response to premium rates when facing different expected indemnity payments (Goodwin 1993). Specifically, farmers who expect to receive larger indemnity payments are less responsive to increases in premium rates. Following the approach employed by Goodwin (1993) and Goodwin et al. (2004), we include premium rates, a measure of expected indemnity payments (i.e., the average loss ratio for the preceding six years of experience in the county) and an interaction term for the loss ratio and the premium rate.

For given premium rates and indemnity payments, risk-averse farmers should also exhibit a higher demand for insurance if they face a higher yield risk. To capture the yield risk faced by the producer, we also include the coefficient of variation of county average yields. In addition to expected payments, costs, and risk, the decision to purchase crop insurance should be dependent on the quality of the land on which the potentially insured crop is grown. High quality land may encourage the purchase of insurance since the yield (and thus potential crop loss) would be larger on higher quality land. A case could also be made that higher quality land would reduce insurance purchases since the likelihood of a yield shortfall would be reduced. To capture the quality of land, we include the percentage of cropland in USDA land capability classes 1 and 2. In addition to the inherent productivity of the land, Wu (1999) found that soil erosion had a positive impact on crop insurance demand. To capture the impact of perceived reductions in soil quality due to erosion, we include the Universal Soil Loss Equation (USLE) measure for 1987 for the 1990-1995 period and the USLE for 1992 for the 1996-2000 period. We also include the planted acreage of that crop in the insurance demand equation, since the amount of liability purchased, and thus insurance participation, should also be a function of the amount of land devoted to the production of that crop.

Fertilizer/chemical applications help determine the crop yield and the variance of crop yield. As discussed in section 3.3, no consensus has developed concerning the impact of fertilizer/chemical expenditures on the demand for crop insurance. To capture this impact, we include county-level fertilizer/chemical expenditures for each year in our study. Two limitations associated with this data should be mentioned. The data does not separate fertilizer and pesticide expenditures, so the separate impacts cannot be studied.[27] In addition, the expenditures are not crop-specific. We cannot take into account different application rates across different crops. While these issues are of concern, the lack of reliable crop-specific data at the level of aggregation (i.e., county) and across the large geographic area used in this study justify the use of the county expenditure data.

In addition to the return to insurance, the yield risk, and the quality of land, the demand for crop insurance is also a function of the farmers' degree of risk aversion and the overall financial structure of the enterprise. Specifically, the decision to insure should depend on the ability of the farmer to diversify risk, the overall farm assets, and borrowing or liquidity constraints that may result in mandatory insurance purchases to obtain credit. While empirical results are inconsistent concerning the impact of farm diversification on crop insurance demand, there is a theoretical justification for expecting that this variable should have an impact on crop insurance demand. A more diversified farming enterprise may have less incentive to purchase crop insurance since they have a greater range of assets with which to absorb a revenue shortfall associated with the production of one or more crops. The level of diversification may also be positively correlated with the demand for crop insurance if both are indicative of the adoption of more "sophisticated" management practices.[28] To account for this effect, we include the county average percentage of income generated from livestock sales as a measure of farm diversification.[29] If a county generates a large proportion of total sales from livestock production, this may indicate that the land in the county is comparatively less productive in crop production. Therefore a positive relationship between insurance participation and the percentage of income derived from livestock sales may simply be a reflection of the comparative risk associated with crop production.

In order to obtain a loan from a bank or other lending institution, farmers are

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[27] This could be a potential issue if the impacts work in opposite directions as reported in the results obtained by Nimon and Mishra (2001).

[28] The adoption of more "sophisticated" management practices are likely a function of education and farming experience.

[29] While individual farms that grow a particular crop may not also raise livestock, our unit of observation is at the county level and most counties in our sample report significant livestock sales. For example, livestock sales ranged from 18.4 to 47.8% of gross sales during the 1996-2001 period. Even at the farm level, it is not unusual to find farming enterprises that raise livestock in addition to growing one of the crops in our study. For example, 47% of farms that grew soybeans in the Southern Seaboard region also raised livestock, while 17% of farms in the Mississippi Portal region grew soybeans and raised livestock (Foreman and Livezey 2002).

often required to purchase crop insurance. To model this requirement, we would like to use a variable, such as the debt-to-asset ratio, that captures the farmer's ability to repay the loan or a measure of debt financing that reflects the actual borrowing. Since we employ county-level annual data, we are unable to find such a measure; therefore, we include a 5 year average of lagged county net farm income to proxy for required insurance purchases imposed by lenders. We hypothesize that a lower net income stream would encourage borrowing, and therefore increase the likelihood that the borrower would face insurance purchase requirements set by the lender. The availability of ad hoc disaster payments should also impact the decision to purchase crop insurance since they act as a free, though non-guaranteed, form of insurance. While we lack sufficient data to construct expected disaster payments for the earlier period, we include a 5 year average of lagged disaster payments in the 1996-2000 period to account for the possibility that ad hoc disaster payments will act as a substitute for purchased crop insurance. We also include annual dummy variables for both periods of our study. Finally, we include a regional dummy variable ($DSOUTH$) in our Southern Seaboard/Mississippi Portal model to capture differences between the two regions. Therefore, the crop insurance demand equation in our model can be summarized as follows:

$$\begin{aligned} INSPART_i = \; & b_0 + b_1 \cdot PREM_i + b_2 \cdot LR_i + b_3 \cdot PREM_i * LR_i + \\ & b_4 \cdot CVYLD_i + b_5 \cdot ACRES_i + b_6 \cdot LSTOCK \\ & + b_7 \cdot NETINCOME + b_8 \cdot LCC + b_9 \cdot CHEMEX \\ & + b_{10} \cdot USLE_{t-1} + b_{11} \cdot YRDUM + b_{12} \cdot DISASTER \\ & + b_{13} \cdot DSOUTH + b_{14} \cdot COUNTYSZ + \epsilon_i \end{aligned} \tag{3.1}$$

where $INSPART$ is insurance demand (participation) for crop i, $PREM$ is the crop insurance premium rate for crop i, LR is the loss ratio for crop i, $PREM * LR$ is an interaction term conditioning the impact of the premium rate on the loss ratio, $CVYLD$ is the coefficient of variation of mean yield for crop i, $ACRES$ is the acreage planted to crop i, $LSTOCK$ is the percentage of total farm sales derived from livestock sales, $NETINCOME$ is a 5 year lagged average of net farm income, LCC is the percentage of cropland in the county in land classes 1 and 2, $CHEMEX$ is the fertilizer/chemical expenditures, $USLE_{t-1}$ is a measure of past soil erosion, $YRDUM$ are the annual dummy variables, $DISASTER$ is a 5 year average of lagged disaster payments, $DSOUTH$ is a dummy variable representing the Southern Seaboard region, $COUNTYSZ$ is the size of the county in acres, and ϵ_i is an error term.

The most difficult issue in modeling the farmer's acreage response decisions is to incorporate the impact of government policies in the decision process. This is often very difficult since there are a large number of policies that affect the farmer's land allocation choices (see section 1.1 for a discussion of relevant policies). In addition, these policies may vary by crop and the provisions may change frequently over time.[30] Although these policies affect acreage and crop mix choices, their individual effects are not the focal point of our study. Since the focal point of our study is to assess the impact of federally-subsidized crop insurance on acreage response, we include annual dummy variables to capture the impact of changes in policy parameters over time. These dummy variables should also capture other influences, such as output and input prices, that exhibit variation across time but little variation across space (at least within homogeneous growing regions).

To determine if an explicit modeling of prices and government policies would change our basic results, we also estimate alternative acreage equations which include expected output prices (or revenue) and government policy parameters. To account for price expectations in the 1990-1995 period, we include the planting time price of a harvest time futures contract for cotton and soybeans.[31] The futures contract prices are then adjusted to reflect state basis differences. Since no futures market exists for grain sorghum, we include the one year lagged state-level harvest time price as a proxy for the expected sorghum price. For every crop except soybeans (the only non-program crop in our study), we further adjust the expected market price by including the USDA projected target price-based deficiency payments to account for the impact of the price supports provided during this period.

To account for price expectations in the 1996-2000 period, we employ the same approach for the market component of the price. Although target price-based deficiency payments were eliminated in the 1996 FAIR Act, price protection was provided by the continuation of the marketing loan program. If the county loan rate exceeds the posted county price (PCP), the grower will receive a loan deficiency payment (LDP) equal to the difference in the loan rate and PCP. This effectively ensures that the grower will receive

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[30] During the period of this study (1990-2000), substantial changes occurred in the focus of U.S. agricultural policy. Attempts were made to reduce government price supports and encourage farmers to base their land allocation choices on market price signals. In order to mitigate against the increase in income risk inherent in the reliance on market prices, efforts were made to increase crop insurance participation by increasing subsidy payments for federally-subsidized crop insurance.

[31] We use the February price for a December futures contract. An alternative specification that included the average of the February, March, and April prices for a December futures contract yielded similar results.

the county loan rate as a minimum payment for a unit of production. To account for this, we use the higher of the county loan rate and the expected market price as the expected price for grain sorghum and soybean producers. Upland cotton production is eligible for LDP payments also, but the payment is based on the difference between the loan rate and the Adjusted World Price (AWP), instead of the posted county price. To account for this difference, we construct an expected LDP payment as the difference between the loan rate and the AWP. If the loan rate is above the AWP, the projected LDP will be positive, otherwise it will be zero. We then add this projected LDP rate to the expected market price to proxy for the expected price facing the cotton grower.

In addition to the inclusion of expected prices, we also estimated a second alternative to the dummy variable approach whereby we replaced expected prices with expected revenue. To construct expected revenue for each crop, we multiplied our expected price for that crop by a 5 year lag of county average harvested yields for that crop. While our major findings are robust to acreage response model specification, we will discuss any differences as we report our results from our preferred specification, i.e., the annual dummy variable approach.

In addition to the impact of deficiency payments (target price and loan), other government policies should contribute to acreage allocation decisions. To be eligible for the target price-based deficiency payments, farmers were required to maintain a base acreage in the program crop. In addition, they were required to remove a portion of that base acreage from production through the Acreage Reduction Program to maintain program eligibility. In our expected price and expected revenue specifications, we included a variable ($ACDIVER$) to capture this acreage diversion requirement for each program crop during the 1990-1995 period. The $ACDIVER$ variable is the product of the ARP rate and the base acreage of the crop.[32] As with other government policies, we used annual dummy variables to capture this impact in our preferred specification.[33]

While we did not explicitly model government policy parameters in the earlier period, concerns (see Goodwin and Mishra (2003)) have been raised as to the impact of post-FAIR policies on acreage allocation. Therefore, we include relevant policy variables in

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[32] Since county base acreage data were not available, we construct a proxy measure from the state base acreage data. We take the ratio of state base acreage to state total planted acreage, then we multiply this ratio by county planted acreage to derive an estimate of the county base acreage. This implicitly assumes that the ratio of base acreage to planted acreage is the same in each county as in the state as a whole.

[33] The impact of base acreage should also be captured in the lagged acreage of the crop. We included lagged acreage in all three model specifications.

our dummy variable specification, in addition to our other two model specifications, in the 1996-2000 period. While base acreage and ARP requirements were eliminated in the FAIR Act, the federal government continued to provide income supports based on historical base acreage. Production Flexibility Contract (PFC) payments, also known as AMTA payments, are based on historical base acreage, though they are not tied to current production. Hennessy (1998) has pointed out that "decoupled" payments, such as AMTA, may still impact production decisions if they change the farmer's degree of risk aversion by altering wealth. If the farmer exhibits decreasing absolute risk aversion (DARA) preferences, then increases in wealth will lead the farmer to accept more risk. Goodwin and Mishra (2003) also point out that these payments may reduce the liquidity and borrowing constraints facing the farmer, and thus may encourage the acceptance of more risk. Even though the impact may be small due to the size of the AMTA payment relative to the average assets of the typical farmer, the effects may not be trivial. To account for this possibility, we include county average AMTA payments ($AMTA$) in our acreage response equation for the 1996-2000 period.

During the 1996-2000 period of our study, ad hoc Marketing Loss Assistance (MLA) payments were made available to compensate farmers for low market prices. While the payments were ad hoc, the willingness of the government to provide these payments signalled farmers that they could expect such ad hoc support in the face of adverse market conditions. Therefore, we include lagged MLA payments (MLA_{t-1}) to take into account the impact on planted acreage of any expectations of future MLA or other ad hoc payments. Although federally-subsidized crop insurance was intended to replace ad hoc disaster payments, these payments have continued during this period. While they are ad hoc in nature, the frequency with which they have been made available may alter producer expectations (as in the case of MLA payments) concerning future benefits. To capture this expectation, we include a 5 year lag of county average disaster payments ($DISASTER$).

In all of our specifications, we include the lagged acreage of the crop ($LAGACRES_i$). This variable should capture crop rotation issues and the adjustment costs associated with altering crop mix. This variable may also capture the impact of the base acreage requirements in the 1990-1995 period. Since the focal point of this section of our study is to determine the impact of crop insurance on acreage allocation, we include our measure of crop insurance participation ($INSPART_i$) as an explanatory variable in our acreage response equations. The amount of acreage planted and the crop mix will also depend on the quality of the land available to the farmer. Low quality land, (i.e., land with low soil productivity) will be less attractive for use in crop production, and therefore one would expect a positive relationship between land quality and crop acreage. The magnitude of this relationship may vary by crop since the yields of some crops are more sensitive than others to measures of soil productivity. To capture this effect, we include the percentage of cropland in USDA land capability classes 1 and 2 to proxy for land quality. In addition to the present productivity of the land, a forward-looking farmer will take into account the impact of present production decisions on future land productivity. To capture the potential productivity losses associated with soil erosion, we include lagged soil erosion in our acreage response equations. To capture "scale" effects on production, we also include total county acreage in our acreage response equation. As previously discussed, we include annual dummy variables to capture the price effects in our model. While their inclusion in lieu of explicitly modeling input and output prices does not permit us to separate the effects, our major focus is on the impact of crop insurance on planted acreage, not the price effects. Finally, we include a regional dummy variable ($DSOUTH$) in our Southern Seaboard/Mississippi Portal model to capture differences between the two regions.

Therefore, the acreage response model in the dummy variable specification can be given by the following equation:

$$\begin{aligned} ACRE_i = \ & b_0 + b_1 \cdot LAGACRES_i + b_2 \cdot INSPART_i + b_3 \cdot LCC + b_4 \cdot USLE_{t-1} \\ & + b_5 \cdot COUNTYSZ + b_6 \cdot YRDUM + b_7 \cdot DSOUTH + b_8 \cdot AMTA \\ & + b_9 \cdot MLA_{t-1} + b_{10} \cdot DISASTER + \epsilon_i \end{aligned} \tag{3.2}$$

where $LAGACRES_i$ is the lagged acres of crop i, $INSPART_i$ is the insurance participation for crop i, LCC is the percentage of cropland in the county in land classes 1 and 2, $USLE_{t-1}$ is lagged soil erosion, $COUNTYSZ$ is the size of the county in acres, $YRDUM$ are annual dummy variables, $DSOUTH$ is a dummy variable representing the Southern Seaboard region, $AMTA$ is the per acre AMTA payments, MLA_{t-1} is per acre lagged MLA payments, and $DISASTER$ is per acre lagged disaster payments, and ϵ_i is an error term.

The above specification does not include AMTA payments, expected MLA payments, or expected disaster payments in the 1990-1995 period. The above model is altered to include the expected prices or expected revenues for each crop (cotton and soybeans in the Southern Seaboard/Mississippi Portal region or cotton and grain sorghum in the Prairie Gateway region) in our price and revenue model specifications. In addition, we also include the acres diverted from production due to the Acreage Reduction Program for cotton and grain sorghum in the 1990-1995 period in our price and revenue models.

Since chemical expenditures are included as regressors in the crop insurance equations, we include an equation to model the determinants of chemical expenditures.[34] As previously mentioned, concerns have been raised as to the impact of the risk reduction effects of crop insurance on input use, i.e., the moral hazard issue. To test this impact, we include insurance participation variables for the crops under consideration. While the total level of chemical and fertilizer expenditures should increase as total planted acreage increases, the magnitude of the increase will depend on the particular crop that is planted.[35] To capture the possible differential impact by crop, we include the crop acreage for both crops in our input use equation.

The total chemical expenditure will also depend on the number of applications, which will depend on the success of previous applications (particularly with regard to pesticides). If chemicals leach into the soil, they may become ineffective and require additional applications (and thus expenditures). To model this possibility, we include a variable to capture the average potential of the soil to facilitate leaching ($AVGLEACH$). We also include the organic matter content (OM) and and the percentage of land in USDA land capability classes 1 and 2 (LCC) as proxies for measures of soil productivity. While our data does not allow for temporal differences in soil productivity, they should help explain some of the spatial differences in chemical expenditures. For example, soils high in organic matter content require smaller expenditures of fertilizers, so counties with soil that is high in organic matter content should have lower chemical expenditures than counties where the soil is low in organic matter content. Therefore, the input use equation can be stated as follows:

$$\begin{aligned} CHEMEX = \; & b_0 + b_1 \cdot INSPART_i + b_2 \cdot INSPART_j + b_3 \cdot ACRES_i \\ & + b_4 \cdot ACRES_j + b_5 \cdot OM + b_6 \cdot AVGLEACH + b_7 \cdot LCC \\ & + b_8 \cdot YRDUM + b_9 \cdot DSOUTH + \epsilon_i \end{aligned} \tag{3.3}$$

where $CHEMEX$ are county expenditures on chemicals and fertilizers, $INSPART_i$ is the insurance participation for crop i, $INSPART_j$ is the insurance participation for crop j,

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[34] We do not have separate data on fertilizer and pesticide expenditures. In addition, expenditure data by crop is not available at the level of aggregation used in this study. While the USDA constructs annual crop input expenditure estimates by farm resource region, this data would fail to account for variation across space (unlike the county-level average chemical expenditures used in this study).

[35] It is also possible that an increase in the acreage of a crop (soybeans, for example) with low chemical requirements may actually lower total expenditures.

$ACRES_i$ is the acreage of crop i, $ACRES_j$ is the acreage for crop j, OM is the average organic matter content on cropland in the county, $AVGLEACH$ is the county average potential for chemical leaching, LCC is percentage of cropland in the county in land capability classes 1 and 2, $YRDUM$ are annual dummy variables, $DSOUTH$ is a dummy variable representing the Southern Seaboard region, and ϵ_i is an error term.

3.4.3 Estimation Procedure and Data

Our empirical analysis employs pooled cross-sectional, time-series data from three USDA farm resource regions during the 1990-2000 time period. A number of estimation issues arise when dealing with this type of pooled data. A number of factors (e.g., cropping history; soil characteristics) vary across counties, so cross-sectional heteroscedasticity may be a problem. There are also a number of factors (e.g., soil characteristics) that affect a specific crop within an area over time, so autocorrelation may be a potential problem. Finally, disturbances which affect crops often reflect common factors (e.g., climate; government policy parameters), and thus raise the possibility that cross-sectional or contemporaneous correlation exists between the error terms for different crops in the same county and year (Wu and Brorsen 1995).

We conducted White tests for heteroscedasticity, and found the presence of heteroscedasticity of an unspecified form in almost all of the equations.[36] As previously mentioned, it is also likely that correlation patterns exist across years for individual counties. To correct for these problems, we ordered our data within each county by time and applied the nonparametric autocorrelation and heteroscedasticity consistent estimation procedures outlined in Newey and West (1987). By construct, our model also contains endogenous variables in all of the equations in our model. Given the endogeneity of key variables and the problems associated with the potential presence of heteroscedasticity and correlation of unknown forms, we employ instrumental variables techniques within the context of the generalized method of moments (GMM).

Data were collected from a wide variety of sources. Insurance program data were taken from the RMA's unpublished county level "summary of business" database. An important caveat associated with the use of such data should be noted at this point. Ex-

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[36] We did not find evidence of heteroscedasticity in the sorghum insurance participation and input use equations in the 1990-1995 Prairie Gateway model.

perience data are available only for those farms that actually purchased insurance. Thus, to the extent that nonbuyers faced higher rates than buyers, our premium rates may understate the actual rates faced by the entire insurance pool. This criticism is relevant to most other empirical studies of insurance demand and participation (Goodwin et al. 2004). The county level yield and acreage statistics were collected from the National Agricultural Statistics Service (NASS). In addition, county-level price data were collected from NASS, while the futures price data were collected from the Bridge database. Input usage and farm sales statistics were taken from the U.S. Department of Commerce's Regional Economic Information System (REIS) database. Projected target price-based deficiency payments were taken from unpublished USDA sources. County loan rates were taken from data provided by the Farm Service Agency (FSA). The cotton Adjusted World Price (AWP) data were taken from various issues of the Cotton and Wool Outlook, a publication of the USDA. Farm acreage data were contained in the 1992 and 1997 editions of the Census of Agriculture. The land characteristic variables were taken from the 1987, 1992, and 1997 NRCS National Resource Inventory (NRI) database. The organic matter content measure was contained in the SOILS-5 database. All nominal economic variables were inflated to 2001 terms using the producer price index.

3.5 Results

3.5.1 Overview

Since we look at a 2 crop model for two resource regions and two time periods, a brief summary of the results pertaining to the central issues in our study is warranted. While a detailed discussion of our results follow, Tables 3.1 and 3.2 present a summary of the findings for our 3 central questions - the impact of premium rates on insurance participation (Insurance Response), the impact of insurance participation on planted acreage (Acreage Response), and the impact of insurance participation on chemical/fertilizer expenditures (Input Use Response). A negative sign indicates a statistically significant (at the 10% level) negative relationship, a positive sign indicates a statistically significant positive relationship, and a zero indicates an insignificant relationship.

Table 3.1: Summary of Results: Southern Seaboard/Mississippi Portal Region

Issue	1990-1995		1996-2000	
	Cotton	Soybeans	Cotton	Soybeans
Insurance Response	-	0	+	+
Acreage Response	-	0	+	-
Input Use Response	-	+	0	0

The + sign indicates a significant positive relationship at the $\alpha = .10$ level.
The − sign indicates a significant negative relationship at the $\alpha = .10$ level.
The 0 indicates an insignificant relationship at the $\alpha = .10$ level.

Table 3.1 presents the results for the 1990-1995 and 1996-2000 periods for cotton and soybean production in the Southern Seaboard/Mississippi Portal region. In the 1990-1995 period, increases in the crop insurance premium rates are associated with a significant decrease in cotton insurance participation, while having no significant impact on soybean participation. In the 1996-2000 period, participation rates increase with increases in premium rates for both crops. While this may seem counter-intuitive, the addition of revenue insurance during this period provides a likely explanation for this result.[37] The results with respect to the impact of crop insurance participation on planted acreage are mixed. Increases in cotton insurance participation are associated with decreases in planted acreage in the 1990-1995 period and increases during the 1996-2000 period. While increases in soybean participation exhibited no significant impact on acreage in the 1990-1995 period, increases in insurance participation are associated with decreases in acreage in the 1996-2000 period. Finally, increases in insurance participation are associated with significant increases (decreases) in chemical and fertilizer use for soybeans (cotton). The impact on input use in the 1996-2000 period was insignificant for both crops. These results provide little support for the moral hazard concerns often raised in the literature.

Table 3.2 presents the results for the 1990-1995 and 1996-2000 periods for cotton and sorghum production in the Prairie Gateway region. As in the previous region, increases in premium rates are associated with lower cotton insurance participation during the 1990-1995 period. The results are insignificant for sorghum (1990-1995) and cotton (1996-2000). Consistent with the soybean and cotton results in the Southern Seaboard/Mississippi Portal region, higher premium rates are associated with higher sorghum insurance participation during the 1996-2000 period. Unlike the mixed results obtained in the Southern

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[37] A detailed discussion of possible explanations of this finding is provided in our later discussions.

Seaboard/Mississippi Portal region, increases in insurance participation during the 1996-2000 period are associated with increases in planted acreage for both crops. In the earlier period, sorghum insurance participation also exhibits a significant positive impact on planted acreage. Increases in cotton insurance participation is associated with lower chemical expenditures in both time periods, though sorghum insurance participation is associated with lower chemical expenditures only in the 1990-1995 period.

Table 3.2: Summary of Results: Prairie Gateway Region

Issue	1990-1995		1996-2000	
	Cotton	Sorghum	Cotton	Sorghum
Insurance Response	-	0	0	+
Acreage Response	0	+	+	+
Input Use Response	-	-	-	0

The + sign indicates a significant positive relationship at the $\alpha = .10$ level.
The $-$ sign indicates a significant negative relationship at the $\alpha = .10$ level.
The 0 indicates an insignificant relationship at the $\alpha = .10$ level.

3.5.2 Southern Seaboard/Mississippi Portal (1990-1995)

Table A.17 contains the GMM estimates for our Southern Seaboard/Mississippi Portal region model. As expected, the insurance demand equations indicate a negative relationship between insurance participation and the premium rate for both crops, though the result was not significant for soybean participation. Insurance demand for both crops is inelastic with respect to the premium rate. At the data means, the elasticities are -.128 (soybeans) and -.132 (cotton). As would also be expected, insurance purchases increase with increases in the coefficient of variation of mean yield. This indicates that crop insurance may be seen as a means to protect against yield risk. Expected indemnity payments, as proxied by the county average loss ratio, is positively related to insurance purchases for soybeans and cotton, though neither are significant at the 10% level. We also find that higher expected indemnity payments decrease the agent's responsiveness to premium changes for both crops, though the impact is significant only for cotton.

Our results indicate that soybean acreage is positively related to soybean insurance purchases. As pointed out in Goodwin (1993), this could be a result of increased incentives on the behalf of agents working on commission to sell insurance to larger farms. On the other hand, more acreage could simply imply more foregone production (and thus income), and therefore the grower could be insuring against a greater revenue loss if more acreage were planted to a particular crop. Cotton acreage exhibited no significant impact on insurance participation. County size exhibits a significantly positive correlation with insurance purchases for cotton, though not for soybeans.[38] A lower net income in the preceding 5 year period is correlated with higher insurance purchases for both crops. This result is consistent with our argument that lower net income may induce agents to increase borrowing, and therefore mandatory insurance purchase requirements associated with credit availability led to an increase in the demand for crop insurance. Counties (farms) with a higher ratio of livestock sales to total sales, a measure of enterprise diversification, are more likely to purchase cotton and soybean insurance. Areas that have a larger percentage of sales derived from livestock may have a comparative disadvantage in crop production resulting from higher expected risk or lower expected returns (Goodwin et al. 2004). This result could also reflect a belief that diversification and insurance purchases are components of "good" farm management.

Our results indicate that soybean producers with greater chemical and fertilizer expenditures tend to purchase more insurance, while there was no significant relationship for cotton producers. It is difficult to draw conclusions concerning this relationship since the chemical and fertilizer expenditure data are not specific to the crop under consideration. In the soybean case, farms (counties) with land that is more suitable to agricultural production tended to purchase less crop insurance. The relationship is positive but insignificant in the cotton case. The soybean result may reflect the perception that more productive land is less likely to experience sufficient yield shortfalls to trigger indemnity payments. Surprisingly, counties with higher levels of past soil erosion tend to purchase less crop insurance. The annual dummy variables are generally negative and of mixed statistical significance, though the 1995 dummy variable exhibited a significant positive impact on insurance purchases for both crops. This is likely a result of the requirement imposed in 1995 that producers receiving other government program payments were required to purchase crop insurance as a condition for continued eligibility in those agricultural support programs. Finally, the regional dummy variable ($DSOUTH$) indicates that soybean insurance participation is

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[38] Average farm size in the county was used in place of county acreage in an alternative specification. The results were robust to the choice of scale variable.

lower in the Southern Seaboard region than in the Mississippi Portal region, controlling for the other factors in the model. The opposite results occur with respect to cotton insurance participation.

The focus of our analysis is on the impact of crop insurance purchases on planted acreage.[39] Increases in soybean insurance participation had a positive (though statistically insignificant) impact on planted acreage. Contrary to expectations, increases in cotton insurance participation are associated with less planted acreage. While the coefficient estimates are of mixed signs and significance, the magnitudes of the elasticities are relatively small.[40] At the data means, the elasticities are .014 for soybeans and -.104 for cotton, respectively. While the sign on the cotton insurance participation is unexpected, the magnitudes of the elasticities are consistent with those reported in Goodwin et al. (2004) for corn and soybean production in the "Heartland" region. Although the expected price and revenue specifications generated elasticities that are higher for soybeans (.050) and lower for cotton (-.012), the differences in magnitude do not alter the conclusion that the demand is very inelastic in each case.

Lagged acreage is included in each equation to capture the impact of partial adjustment effects. This should also capture the impact of base acreage requirements during this period. Lagged acreage is positive and highly significant in both acreage response equations. In particular, the cotton result may reflect the high fixed costs associated with moving out of cotton production. Lagged soil erosion does not have a statistically significant impact on planted acreage for either crop. The quality of land, proxied by the percentage of cropland in USDA land capability classes 1 and 2, had a significant positive impact on cotton acreage, but is associated with lower soybean acreage. The annual dummy variables are of mixed signs, though they are statistically significant in most cases. As previously mentioned, these dummy variables should capture the impact of input prices, output prices, and government policy changes that vary over time but not space. The regional dummy variable indicates that statistically significant differences exist between the Southern Seaboard and Mississippi Portal regions with respect to crop acreage. Specifically, the dummy variable indicates that, controlling for the other variables, soybean acreage is higher in the Mississippi Portal region,

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[39] It should be noted that our analysis does not distinguish between increases in crop acreage due to the transfer of acreage between crops or the cultivation of previously uncultivated cropland.

[40] While the expected price specification also generated a significant negative relationship between acreage and cotton insurance participation, the coefficient in the expected revenue specification is insignificant. In all 3 cases, the magnitudes of the elasticities are very similar.

while cotton acreage is higher in the Southern Seaboard region.

In the expected price specification, the coefficients on the expected prices are not consistent with economic theory.[41] These expected price results are robust to the method of formulation. Specifically, futures prices (with and without basis adjustments) and lagged historical prices yield the same results. This pattern continues even if we use expected market prices (i.e., remove the impact of expected deficiency payments). These results are likely a function of the limited variability in our price data. Since most of the variation in our model is cross-sectional (a large number of counties over a few years), little price variation across space (particularly within homogeneous growing regions) may limit our ability to model price response. Having said that, the substitution of expected revenue for expected prices yields more theoretically viable results. While both signs in the soybean acreage equation are positive, only the soybean expected revenue is significant. In the cotton acreage equation, the signs are again positive, but only the expected revenue associated with cotton production is significant.

This difference between the use of expected revenue as opposed to expected prices is generally constant across regions and time periods. The use of expected revenue is likely superior to the use of expected prices in farmer's planting decisions in that the revenue formulation takes into account differences in crop yield. Regardless of the model specification, the impact of crop insurance on planted acreage, though statistically significant in some cases, yield responses of a very small magnitude. The model specification choice also did not alter the results with respect to the other explanatory variables in most cases.

Our results from the input use equation generated mixed results with respect to the moral hazard issue. Farms (counties) that purchase more cotton insurance tend to purchase less chemicals and fertilizers. This adds support to the findings in Goodwin (1993), Goodwin and Smith (2003), and Goodwin et al. (2004). On the other hand, higher soybean insurance purchases are associated with higher chemical/fertilizer use. While an increase in cotton acreage is associated with increases in chemical and fertilizer expenditures, an increase in soybean acreage is associated with decreases in expenditures. This is reasonable since soybean production is less chemical-intensive than cotton production. Having said that, it should again be noted that our expenditure data are not crop-specific, so we

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[41] In the soybean acreage equation, the signs on both expected prices are positive, though only the sign on the expected price of cotton is significant. More perplexing is the result that the expected cotton price exhibits a negative relationship with cotton acreage, while the expected soybean price exhibits a positive relationship.

must be careful when drawing conclusions. The land productivity measure exhibits a positive, though insignificant, relationship with chemical expenditures, while land with greater leaching potential is associated with a decrease, though statistically insignificant, in expenditures. The positive relationship between land capability class and expenditures may reflect the greater likelihood that production (and therefore chemical expenditures) will take place on higher quality land. The annual dummy variables are of mixed signs and significance, though the regional dummy variable indicates that chemical/fertilizer expenditures are significantly higher in the Southern Seaboard region.

To evaluate the impact of insurance participation on crop acreage, we conduct simulations whereby we exogenously reduce premium rates from their mean values and then use our structural model to evaluate the impact on crop insurance participation and crop acreage.[42] Specifically, we reduce each crop premium rate by 30% while holding the other premium rates constant. In addition, we simulate the impact of an "across-the-board" reduction of 30% for all 3 crops. All other variables in the model are held constant at their mean values, except the loss ratio which is allowed to increase as the premium rate decreases (i.e., the premium subsidy increases).

The results from the simulation are presented in Table A.19. A 30% across-the-board premium rate reduction increases insurance participation by 15.27% and 9.85% for soybeans and cotton, respectively. Even with the statistically significant changes in soybean and cotton insurance participation, there is a very small response in soybean acreage (0.21%), though the response is somewhat higher for cotton (-1.06%). Similar results occur when we reduce the premium rates for one crop while holding the premium rates of the other two crops constant. For example, a reduction in soybean insurance premium rates by 30% increases soybean insurance participation by 17.66%, but increases soybean acreage by only 0.24%. Reductions in cotton insurance premium rates generate results that are similar to those with respect to a 30% rate reduction for both crops. Given an annual average of 11.04 million acres planted to soybeans in the Southern Seaboard/Mississippi Portal region during this time period, a 0.21% increase in acreage would translate to only an annual average of an additional 26 thousand soybean acres. On an average annual base of 5.4 million acres, a decrease in cotton acreage of 1.06% would lead to a decrease of approximately 57 thousand acres. While these changes are not trivial, they are quite small compared to the

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[42] A reduction in the premium rate is analogous to an increase in premium rate subsidies, since the net premium rate is the producer-paid premium rate minus the premium rate subsidy.

total acreage planted to each crop in this combined region.

3.5.3 Prairie Gateway(1990-1995)

Table A.18 contains the GMM estimates for our Prairie Gateway region model. The insurance demand equations indicate a statistically significant negative relationship between insurance participation and the premium rate for cotton, while the relationship is insignificant (though negative) for sorghum. Insurance demand for both crops is inelastic with respect to the premium rate. At the data means, the elasticities are -.065 for grain sorghum and -.199 for cotton. The expected revenue specification contained a slightly lower elasticity (-.117) for cotton, though the results were virtually identical for sorghum. As in the previous region, insurance purchases increase with increases in the coefficient of variation of mean yield. Expected indemnity payments, as proxied by the county average loss ratio, are positively (though not significantly) related to sorghum insurance purchases, though suprisingly exhibiting a significant negative impact on cotton insurance purchases. We also find that higher expected indemnity payments decrease the agent's responsiveness to premium changes for both crops. This finding adds support to the claim of Goodwin (1993) that agents condition their response to changes in the premium rate on their expected indemnity payments.

As in the soybean results in the previous region, our results indicate that increases in the acreage of a crop is positively related to increases in insurance purchases. Again, this could be a result of increased incentives for insurance agents or the impact of greater foregone revenue in the event of a yield shortfall. Unlike our previous results, the scale variable (county acres) is associated with lower sorghum insurance purchases. While county size exhibits a significant positive impact on cotton insurance participation, the sign changes but is still significant in the expected revenue specification. This is one of the few cases where the choice of model specification made a substantial difference in the results. Unlike the previous results, a lower net income in the preceding 5 year period leads to a decrease in insurance purchases. This could indicate that the producer has insufficient assets with which to purchase insurance and that the borrowing constraints are not eliminated by the guarantee of insurance purchases. Counties (farms) with a higher ratio of livestock sales to total sales, a measure of enterprise diversification, were less likely to purchase sorghum and cotton insurance, though the coefficient estimates were insignificant in both cases.

Our results indicate that producers with greater chemical and fertilizer expenditures tend to purchase less cotton and sorghum insurance. Again, it should be noted that it is difficult to draw conclusions concerning this relationship since the chemical and fertilizer expenditure data are not specific to the crop under consideration. In the insurance purchase decisions for both crops, farms with land that is more suitable to agricultural production tend to purchase more crop insurance. This may reflect a belief that land that is better suited to agricultural production will yield higher returns, and thus insurance is purchased to protect against a greater loss. Consistent with the earlier findings, past levels of soil erosion are significantly associated with lower levels of insurance purchases.[43] As in the previous results, the dummy variables are of mixed significance and signs, though the dummy variable for 1995 is significantly positive in all cases.

The focus of our analysis is on the impact of crop insurance purchases on planted acreage. Increases in grain sorghum and cotton insurance participation have a positive impact on planted acreage, though the coefficient estimate is insignificant in the cotton acreage equation. While the results for sorghum are generally consistent with the results for soybeans in the Southern Seaboard/Mississippi Portal region, cotton insurance participation had a positive (though insignificant) impact on cotton acreage, while the impact was negative (and significant) in the Southern Seaboard/Mississippi Portal region. Given these differences, the magnitudes of the elasticities evaluated at the data means are still very small in the case of cotton (.001), though somewhat higher (.211) for sorghum. The elasticities are very similar in the other model specifications, though the sorghum response becomes even more inelastic (.145).[44]

Lagged acreage is included in each equation to capture the impact, among other things, of partial adjustment and base acreage. Lagged acreage is positive and highly significant in both acreage response equations. Lagged soil erosion is associated with a statistically significant decrease in cotton acreage, but a statistically significant increase in sorghum acreage. The quality of land, proxied by the percentage of cropland in USDA land capability classes 1 and 2, had a negative (though insignificant) impact on planted acreage in both crop equations. These results for cotton are inconsistent with the Southern

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[43] An alternative specification conditioned soil erosion on the NRI conservation practice factor to account for management practices aimed at limiting the impact of soil erosion on future land productivity. While the signs were still negative, the level of significance declined if conservation practices were included.

[44] The own and cross-price effects are statistically insignificant in both crop acreage equations. This is consistent with other results in the literature that indicate that crop acreage was less responsive during periods of base acreage requirements.

Seaboard/Mississippi Portal results where land quality was positively associated with cotton acreage. Compared to the omitted year (1990), the annual dummy variables are generally negative and significant. As previously mentioned, these dummy variables should capture the impact of input prices, output prices, and government policy changes over time.

Unlike the mixed results from the Southern Seaboard/Mississippi Portal region, counties (farms) that purchase more sorghum and corn insurance tend to decrease their purchases of chemicals and fertilizers. In both regions, counties that have higher cotton insurance purchases tend to spend less on chemicals and fertilizers. This gives some support to the moral hazard concerns, though again the expenditures are not crop specific. As in our previous results, increases in cotton acreage are associated with increases in chemical expenditures. Unlike the soybean case, increases in grain sorghum acreage are associated with higher chemical expenditures. Unlike the previous results from the Southern Seaboard/Mississippi Portal region, the land productivity measure is negatively correlated with chemical expenditures. This negative relationship between land capability class and chemical expenditures may reflect the need to use less chemicals and fertilizers on more productive land.[45] As expected and contrary to the earlier results, land with greater leaching potential is associated with an increase in chemical and fertilizer expenditures. The annual dummy variables are generally positive, though insignificant in almost every case.

The results from the simulations are presented in Table A.20. A 30% across-the-board premium rate reduction increases insurance participation by 7.12% for sorghum and 8.61% for cotton. Similar results occur when the premium rates are adjusted for one crop while holding the premium rates for the other 2 crops constant. In all cases, changes in cotton acreage are of small magnitude. For example, increases in cotton insurance participation of 8.61% cotton elicited only a .04% increase in cotton acreage. Sorghum acreage is much more responsive to changes in insurance participation. A 30% reduction in sorghum premium rates induce a 6.93% increase in insurance participation and a 1.31% increase in planted acreage. Given an annual average of 7.03 million acres planted to grain sorghum in the Prairie Gateway region during this time period, this would imply an annual increase of approximately 92 thousand acres. On an average annual base of 5.3 million acres, an increase in cotton acreage of .04% would lead to an increase of only 21 thousand

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[45] The use of the expected revenue specification yields a coefficient estimate on land capability class that is positive and significant. In addition, sorghum acreage also exhibits a significant negative relationship with chemical expenditures in this specification.

acres. As in the previous case, the changes in planted acreage are relatively small given the total acreage planted to each crop in this region.

3.5.4 Southern Seaboard/Mississippi Portal (1996-2000)

Table A.23 contains the GMM estimates for our Southern Seaboard/Mississippi Portal region model. Unlike the results in the earlier time period, the insurance demand equations indicate a positive relationship between insurance participation and the premium rate for both crops.[46] While this seems to be an unlikely result, changes that occurred in the insurance program between the two time periods, particularly the introduction of revenue insurance products, may account for this relationship. Goodwin et al. (2004) found that counties with higher revenue insurance purchases (as a proportion of overall insurance purchases) tended to have significantly higher overall levels of participation. Since premium rates are higher for revenue insurance, it is not surprising that this increase in participation associated with increases in revenue insurance purchases are associated with higher premium rates.[47] Finally, the impact of increases in the producer-paid portion of insurance premiums resulting from efforts to reduce loss ratios may have been offset by mandatory insurance purchase requirements set by lending institutions.

Insurance demand for both crops is relatively inelastic with respect to the premium rate. At the data means, the elasticities are .295 (soybeans) and .366 (cotton). While these demands are still inelastic, they are more than double those reported in the 1990-1995 period. As would also be expected, insurance purchases increase with increases in the coefficient of variation of mean yield. This indicates that crop insurance may be seen as a means to protect against yield risk. Expected indemnity payments, as proxied by the county average loss ratio, is positively related to cotton insurance purchases, but negatively related to those for soybeans. We find that higher expected indemnity payments have no significant impact on the agent's responsiveness to premium changes.

Our results indicate that increases in the acreage of both crops is positively related to increases in insurance purchases, though the result is insignificant for cotton. County size exhibits a significantly positive correlation with insurance purchases for cotton, though

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[46] The liability used to construct our insurance participation measure includes both yield (APH) and revenue insurance liability. An effort was made to explicitly model revenue insurance, but the lack of availability in many areas raised a significant problem with degrees of freedom.

[47] Goodwin et al. (2004) also found a positive relationship between premium rates and insurance participation in the 1997-1998 period for the Heartland region.

not for soybeans. A lower net income in the preceding 5 year period is correlated with higher insurance purchases for both crops. This result is consistent with our argument that lower net income may induce agents to increase borrowing, and therefore mandatory insurance purchase requirements associated with credit availability led to an increase in the demand for crop insurance. The percentage of total sales derived from livestock sales had no significant impact on insurance purchases for either crop. Contrary to expectation, lagged disaster payments are associated with higher levels of crop insurance purchases. This may reflect requirements to purchase crop insurance to maintain eligibility to receive disaster payments.

Our results indicate that cotton producers with greater chemical and fertilizer expenditures tend to purchase more insurance, while there was no significant relationship for soybean producers. While these results are inconsistent with those from the earlier period, it is difficult to draw conclusions concerning this relationship since the chemical and fertilizer expenditure data are not specific to the crop under consideration. Counties with a greater proportion of land in USDA land capability classes 1 and 2 tended to purchase less crop insurance, though the impact was only significant in the soybean equation. This result may reflect the perception that more productive land is less likely to experience sufficient yield shortfalls to trigger indemnity payments. Counties with higher levels of past soil erosion tend to purchase less cotton insurance, but not on soybean insurance where the coefficient is insignificant. The annual dummy variables are generally negative and of mixed statistical significance for cotton, though they are all negative and statistically significant for soybeans. Finally, the regional dummy variable ($DSOUTH$) indicates that cotton insurance participation is lower in the Southern Seaboard region than in the Mississippi Portal region, while there is no statistically significant difference between the regions with respect to soybean insurance participation.

The focus of our analysis is on the impact of crop insurance purchases on planted acreage. Increases in cotton insurance participation had a positive and statistically significant impact on planted acreage. Contrary to expectations, increases in soybean insurance participation are associated with less planted acreage.[48] While the coefficient estimates are of mixed signs and significance, the magnitudes of the elasticities are relatively small. At the data means, the elasticities are -.063 for soybeans and .099 for cotton, respectively. In

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[48] While still negative, the coefficient estimate in the expected revenue specification was not significant at the 10% level.

the expected revenue specification, the elasticity is somewhat lower for soybeans (-.004), though it is virtually identical for cotton.

As in all previous cases, lagged acreage is positive and highly significant in both acreage response equations. Lagged soil erosion does not have a statistically significant impact on planted acreage for either crop. The quality of land, proxied by the percentage of cropland in USDA land capability classes 1 and 2, also had no significant impact on the acreage of either crop. The annual dummy variables are of mixed signs and statistical significance. The coefficient estimates on the expected revenue variables in that specification are of the expected signs and all are statistically significant.[49] The use of that specification did not significantly alter any of the acreage response results. The regional dummy variable indicates that statistically significant differences exist between the Southern Seaboard and Mississippi Portal regions with respect to cotton acreage, though no differences exist with respect to soybean acreage.

Lagged disaster payments exhibit no significant impact on the acreage of either crop. While this result is reasonable given the ad hoc nature of disaster payments, the Southern Seaboard and Mississippi Portal region farmers have been frequent recipients of large (relative to those received in other regions) amounts of disaster assistance, so one would believe that if farmers in any region formed expectations concerning the likelihood of future payments it would be farmers in these two regions. Increases in lagged MLA payments are associated with statistically significant increases in cotton acreage and decreases in soybean acreage. On the other hand, increases in AMTA payments are associated with significant increases in soybean acreage, though no significant impact on cotton acreage. One possible explanation of the difference between the impact of AMTA payments on cotton and soybean acreage is that cotton farm operations tend to be much larger than those associated with soybean farming.[50] As a result, AMTA payments may make up a larger percentage of net farm wealth for soybean farmers than for cotton farmers. If the increases in wealth associated with the receipt of AMTA payments lead to decreases in risk aversion, this may encourage farmers to plant on economically marginal land. All other things held constant,

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[49] It should also be noted that the own and cross-price acreage elasticities indicate an inelastic acreage response, though the responses are much higher than those from the 1990-1995 period. This is consistent with findings in the literature that the acreage restrictions of the earlier period reduced the elasticity of acreage response to changes in the expected price (revenue) of the crop.

[50] For example, total household net worth on farms where cotton is the primary crop was $506,582 in the Southern Seaboard region in 1999, while farms whose primary crop was soybeans had a total household net worth of $342,578. This farm financial management data can be found at the USDA website address http://www.ers.usda.gov/data/farmfinancialmgt.

the impact should be more substantial if the AMTA payments make up a larger portion of farm net worth. These results are robust to model specification and are consistent with those from the Prairie Gateway region.

Our results from the input use equation indicate that increases in insurance purchases of either crop exhibit no statistically significant impact on chemical/fertilizer expenditures. While an increase in cotton acreage is associated with increases in chemical and fertilizer expenditures, an increase in soybean acreage is associated with decreases in expenditures. Again, this is reasonable since soybean production is less chemical-intensive than cotton production. The land productivity measure exhibits a positive, though insignificant, relationship with chemical expenditures, while land with greater leaching potential is associated with a statistically insignificant increase in expenditures. The annual dummy variables are all positive and statistically significant (except 1996), and the regional dummy variable indicates that chemical/fertilizer expenditures are significantly higher in the Southern Seaboard region.

The results from the simulation are presented in Table A.25. A 30% across-the-board premium rate reduction reduces insurance participation by 8.95% and 11.23% for soybeans and cotton, respectively. The reduction in insurance participation resulting from a decrease in premium rates is a function of the regression results that indicated a positive relationship between premium rates and insurance participation. Even with the statistically significant changes in soybean and cotton insurance participation, there is a very small increase in soybean acreage (0.63%) and a somewhat larger decrease in cotton acreage (1.13%). Similar results occur when we reduce the premium rates for one crop while holding the premium rates of the other two crops constant. For example, a reduction in soybean insurance premium rates by 30% decreases soybean insurance participation by 8.84%, but increases soybean acreage by only 0.63%. Reductions in cotton insurance premium rates generate results that are similar to those with respect to a 30% rate reduction for both crops.

3.5.5 Prairie Gateway (1996-2000)

Table A.24 contains the GMM estimates for our Prairie Gateway region model. As in the Southern Seaboard/Mississippi Portal region, the insurance demand equations indicate a positive relationship between insurance participation and the premium rate, though the relationship is no longer statistically significant for cotton. Insurance demand for both crops is relatively inelastic with respect to the premium rate. At the data means, the elasticities are .253 for grain sorghum and .183 for cotton. The elasticities generated in the expected revenue specification are almost identical to those in our preferred specification. Sorghum insurance purchases increase with increases in the coefficient of variation of mean yield, but cotton insurances purchases decrease.[51] Expected indemnity payments, as proxied by the county average loss ratio, are positively (though not significantly) related to sorghum insurance purchases, though exhibiting a significant negative impact on cotton insurance purchases. While the cotton result is surprising, it is consistent with the results from the earlier period. We also find that higher expected indemnity payments decrease the agent's responsiveness to premium changes for cotton.

As in the results from the previous region, an increase in cotton acreage is not significantly related to an increase in insurance purchases, though increases in sorghum acreage leads to significant increases in insurance participation. County acreage is associated with lower sorghum insurance purchases, though there is no significant effect on cotton insurance purchases. A lower net income in the preceding 5 year period leads to an increase in sorghum insurance purchases, but no statistically significant impact on cotton participation. Our measure of enterprise diversification, the ratio of livestock sales to total sales, exhibited no significant impact on insurance participation for either crop.

Our results indicate that producers with greater chemical and fertilizer expenditures tend to purchase less cotton and more sorghum insurance. Again, it should be noted that it is difficult to draw conclusions concerning this relationship since the chemical and fertilizer expenditure data are not specific to the crop under consideration. In the insurance purchase decisions for both crops, farms with land that is more suitable to agricultural production tended to purchase more crop insurance. Again, this may reflect a belief that land that is better suited to agricultural production will yield higher returns, and thus insurance is purchased to protect against a greater loss. Consistent with the earlier findings, past levels of soil erosion are significantly associated with lower levels of insurance purchases. As in the previous results, the dummy variables are of mixed significance and signs.

With respect to our acreage response equations, increases in grain sorghum and cotton insurance participation have a positive impact on planted acreage. Evaluated at the

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[51] While statistically significant in the reported results, this negative relationship is insignificant in the expected revenue specification.

data means, the elasticities are .330 for grain sorghum and .080 for cotton. While these elasticities are still very small in magnitude, they are considerably larger than those from the Prairie Gateway region during the 1990-1995 period or the Southern Seaboard/Mississippi Portal region during the 1996-2000 period. These results are consistent with those derived using the other two model specifications.

As in all previous cases, lagged acreage is positive and highly significant in both acreage response equations. Lagged soil erosion is associated with a statistically significant decrease in cotton acreage, but a statistically significant increase in sorghum acreage. The quality of land, proxied by the percentage of cropland in USDA land capability classes 1 and 2, had an insignificant impact on planted acreage in both crop equations. The annual dummy variables are of mixed signs and statistical significance. As previously mentioned, these dummy variables should capture the impact of input prices, output prices, and government policy changes over time. As previously mentioned, the results with respect to the government payment variables -disaster, MLA, and AMTA - are consistent with those generated in the other region. Lagged disaster payments appear to have no effect on acreage decisions, while the impact of lagged MLA and AMTA payments vary by crop.

With respect to our input equation, counties (farms) that purchase more sorghum insurance tend to increase (though not significantly) their purchases of chemicals and fertilizers, while increases in cotton insurance purchases are associated with lower chemical expenditures. Increases in cotton acreage are associated with greater chemical expenditures, while changes in sorghum acreage have little impact on chemical expenditures. Contrary to expectations, land with greater leaching is associated with lower chemical expenditures, while organic matter content and land productivity have no discernible impact on chemical expenditures. The annual dummy variables are generally negative and significant in most cases.

The results from the simulations are presented in Table A.26. A 30% across-the-board premium rate reduction decreases insurance participation 3.88% for sorghum and 17.05% for cotton. Again, the reduction in insurance participation resulting from a decrease in premium rates is a function of the regression results that indicated a positive relationship between premium rates and insurance participation. A 30% reduction in sorghum premium rates induce a positive response in cotton insurance participation and a negative response in sorghum insurance participation, while the opposite results hold for a 30% reduction in cotton premium rates. Since cotton and sorghum acreage exhibit a positive association with insurance participation, decreases in insurance participation associated with premium reductions will also lead to decreases in planted acreage as premium rates fall. This is what we find in our simulations. Decreases in premium rates tend to lower both insurance participation and planted acreage. In addition, the magnitudes of the acreage responses are much higher than in other regions or previous time periods. For example, a 30% reduction in cotton premium rates lead to a 1.76% increase in sorghum acreage and a 1.36% decrease in cotton acreage.

3.6 Conclusions

Major concerns have been raised concerning possible increases in crop acreage resulting from the provision of federally-subsidized crop insurance. Questions have even been raised as to the viability of crop production in many areas, such as upland cotton production in northwestern Texas, without the availability of crop insurance. This question has taken on even more importance since recent increases in subsidy levels may provide even more incentives to increase insurance participation. Recent research into this question has provided mixed and often contradictory results. In addition, crops (e.g., upland cotton) and areas (e.g., Prairie Gateway region) of concern have received very little attention in the literature.

To address these issues, we estimated a multi-equation structural model to evaluate the impact of crop insurance purchases on planted acreage. We looked at two regions (Prairie Gateway and Southern Seaboard/Mississippi Portal) and two time periods (1990-1995 and 1996-2000). We looked at upland cotton in both regions and two major competing crops- grain sorghum in the Prairie Gateway region and soybeans in the Southern Seaboard/Mississippi Portal region. In addition, our analysis accounts for two distinct agricultural policy regimes (pre- and post-FAIR) during our two time periods, thus differences in acreage response between the two periods could capture, among other things, the interaction between crop insurance and other agricultural policies.

Our empirical results suggest that the demand for crop insurance is quite inelastic, though the elasticity increases during the later period. Contrary to expectations, we found a positive relationship between premium rates and insurance participation during the 1996-2000 period. As previously argued, this may be a result of the introduction of revenue insurance products during this period. Increases in overall participation rates occurred as farmers purchased insurance against revenue (as opposed to only yield) shortfalls. Since premium rates for the revenue coverage are higher than those for yield coverage, the positive relationship between insurance participation and premium rates should not be surprising. With respect to the major question that we addressed, the acreage response to insurance participation is also quite inelastic. Grain sorghum acreage is more responsive to insurance participation than the other two crops, but the elasticities only range from .21 (1990-1995) to .33 (1996-2000). The results of our simulations indicate that large premium rate reductions generate significant changes in insurance participation, but those changes do not result in large changes in planted acreage. The largest changes in acreage occur in the 1996-2000 period, where sorghum acreage changes by 1.5-3.3% and cotton acreage changes by 1.1-1.3%. Soybean acreage changes are much more modest than those for cotton and sorghum.

While our results with respect to upland cotton and grain sorghum in these regions indicate that planted acreage may be more responsive to changes in insurance participation than other crops in other regions, our results do not indicate the type of changes found in Griffin (1996) and Keeton et al. (2000). Our major findings are consistent with those in Goodwin et al. (2004) that indicate that substantial changes in insurance participation would have a modest impact on acreage allocation decisions. Having said that, the results, especially those with respect to grain sorghum acreage, suggest that crops other than those that are frequently studied (e.g., wheat, corn, and soybeans) may exhibit different responses to the provision of insurance. As efforts are made to extend coverage to other agricultural commodities, the impact of crop insurance on acreage response should remain a valid empirical question.

Chapter 4

Crop Insurance, Government Agricultural Policies, and Soil Erosion

4.1 Introduction

Concerns about the potential impact of agricultural production on indicators of environmental quality have become prominent in policy discussions and the environmental/economics literature. As discussed in Chapter 3, a number of theoretical and empirical studies have been conducted to analyze the impact of disaster payments, crop insurance, price supports, and acreage retirement programs on land allocation and input use. Many have argued that unintended negative environmental consequences could result from acreage and input use changes in response to government efforts to stabilize farm income and reduce the risk associated with agricultural production. In addition, concerns have been expressed that these programs may be working at cross-purposes with other programs, such as the Conservation Reserve Program (CRP), that are designed to mitigate the effects of the environmental damage resulting from agricultural production activities.

A number of researchers (see Johnson, Wolcott and Aradhyula (1990); Just and Antle (1990); LaFrance (1992); Innes and Ardila (1994)) have recently explored the theoretical connection between government policy, extensive and/or intensive margin changes, and environmental outcomes. In particular, Innes and Ardila provided a theoretical framework in which to study the impact of agricultural insurance on soil depletion. While these studies have contributed to an understanding of the theoretical relationship between production choices and environmental quality indicators, little empirical research has been conducted that attempts to link the impact of government agricultural policies to changes in indicators of environmental quality. The limited research that has occurred has often been conducted over very small geographic areas. This limits the ability to draw general conclusions based on the findings in these studies. On the other hand, researchers who have attempted to study larger geographic areas have often not taken into account the importance of site-characteristics and land heterogeneity.

Soil erosion is one of those key indicators of changes in environmental quality. Soil erosion is defined as the detachment and transportation of soil particles by wind or water activity (Larson, Pierce and Dowdy 1983). The extent of soil erosion on agricultural land is dependent on the specific use of the land (e.g., cultivated vs. noncultivated cropland), the level of cover vegetation, the physical and chemical characteristics of the soil, and the agricultural practices employed on the land. In particular, agricultural practices such as plowing, discing, and planting remove cover vegetation and break down soil structure. The breaking down of the soil structure leads to increases in leaching and surface runoff. Among other things, this increase in leaching and surface runoff accelerates water quality degradation, habitat destruction, and flooding associated with increases in sedimentation. Therefore, soil erosion has a substantial impact on a number of measures of environmental quality. In addition, soil erosion has a direct impact on the future productivity of the land where the erosion occurs. Specifically, soil erosion reduces the future productivity of the soil by reducing plant-available water capacity, reducing plant-nutrient supply, degrading soil structure, and minimizing the impact of chemical applications and other management strategies (National Soil Erosion Soil Productivity Research Planning Committee and Administration 1981).

Several studies (Wu and Babcock (1998); Goodwin and Smith (2003)) have included soil erosion in a structural model of agricultural production. Wu and Babcock included a dummy variable to capture whether or not the farmer had purchased crop insurance, while Goodwin and Smith included other government program payments, in addition to crop insurance, as explanatory variables in their soil erosion equations.[1] While Goodwin and Smith included a measure of aggregate government expenditures as an explanatory variable in their soil erosion model, they failed to account for differences that may exist between the myriad of government programs available to the farmer.[2] For example, payments tied to current production (e.g., loan deficiency payments) may induce production activities that affect soil erosion, while payments that are "decoupled" from current production (e.g., AMTA payments) may provide little incentive to alter production, and thus may have little impact on soil erosion.

Recent research has demonstrated that different agricultural policies may have significantly different impacts on crop mix and planted acreage. Keeton et al. (2000) and Griffin (1996) found substantial acreage increases due to the availability of federally-subsidized crop insurance, while Young et al. (2001b) and Goodwin et al. (2004) found relatively small production increases due to insurance availability. While our results in Chapter 3 indicate that the impact may be small in magnitude, we also find that the impact of crop insurance on planted acreage varies by crop and production region. In addition, we found that payments tied to current production (deficiency payments), decoupled payments (AMTA payments), and ad hoc payments (disaster and Market Loss Assistance payments) exhibit differential impacts on acreage response. Finally, Goodwin and Mishra (2003) and Adams, Westhoff, Willott and Young (2001) found that even decoupled payments may have a statistically significant, though quantitatively modest, impact on planted acreage.

The goal of this chapter is to extend the preliminary efforts of Goodwin and Smith (2003) to explore the impact of government agricultural payment and risk management policies on soil erosion. Instead of using aggregate government payment data, we employ county-level program payment data for a number of different government programs available to the farmer during the years 1992 and 1997. In addition to the government payment data, we employ National Resources Inventory (NRI) and Soils Interpretation Record (SIR) data to provide measures of soil characteristics, management practices, and conservation practices. While soil erosion occurs as a result of both water-induced (i.e., sheet and rill)

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[1] Using an indicator variable having the value of one if the producer purchased crop insurance and zero otherwise, Wu and Babcock found that crop insurance participation had no significant impact on a composite measure of water- and wind-induced soil erosion.

[2] Goodwin and Smith found that their aggregate measure of government payments had a positive impact on soil erosion, while crop insurance participation exhibited a negative, though very small, impact on soil erosion.

and wind-induced factors, we limit our study to sheet and rill erosion.[3] We use the NRI data to estimate the impact of government payments on soil erosion within a 2SLS framework for 1992 and 1997. Although the variation in our data is primarily cross-sectional, we use data from the 3 year period surrounding our 1992 and 1997 time periods in our soil erosion equations to model the expectation of government payments.[4]

This study is organized in the following manner. Section 2 provides a discussion of the relevant literature. Section 3 details the model, estimation procedures, and data used in the study. Section 4 provides a presentation and discussion of the results. A summation of the findings and concluding remarks are presented in the final section.

4.2 Literature

The impact of government policies on changes in environmental quality occur primarily through their impact on cropping practice, input use, and acreage allocation. A body of research exists (for example, Chavas and Holt (1990); Horowitz and Lichtenberg (1994); Wu and Brorsen (1995); Goodwin et al. (2004); and Wu (1999)) that explores the relationship between government agricultural policies and acreage allocation and input use. Another line of research (for example, Pionke and Urban (1985) and Amos and Timmons (1983)) focuses on the impact of input and land use on measures of soil and water quality, though much of this research has centered on the impact on water quality. Research that addresses a direct connection between government agricultural policies and environmental outcomes is relatively sparse (for example, Wu (1999); Goodwin and Smith (2003); and Plantinga (1996)). This literature review will focus on those studies that attempt to link agricultural policies to changes in environmental quality.

The research connecting government agricultural policies and environmental outcomes has been undertaken at various levels of data aggregation (e.g., farm, county, or state). While there has been some research conducted at the farm level that combines economic and environmental factors (for example, Johnson, Adams and Perry (1991) and Wu (1999)), it is difficult to draw general conclusions beyond their limited areas of study.

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[3] Sheet and rill erosion occurs when layers of soil are removed due to the action of rainfall and subsequent runoff activities. We do not model wind-induced soil erosion in our study since almost all of our sample counties are located in areas where wind-induced soil erosion has not been viewed as a problem.

[4] The lack of compatible government payments data before 1990 prevents us from using a longer time-series to model producer expectations concerning the magnitude of unknown government payments.

Alternatively, research has been conducted using economic and environmental data aggregated to the county, state, or region level. This aggregate approach has taken two basic forms. First, aggregate economic models have been integrated with physical models in an effort to link the impact of agricultural policies on production decisions, and then link those production decisions to specific environmental outcomes. Examples of this approach include Mapp, Bernando, Sabbagh, Geleta and Watkins (1994) and Wu, Mapp and Bernando (1996). While not specifically modeling the physical process, the other approach generates measures of changes in environmental outcomes by including site-specific characteristics in an economic model based on a farmer's production decisions (Wu and Segerson 1995). This modeling approach can be found in Wu and Segerson (1995), Wu and Babcock (1998), Goodwin and Smith (2003), and Goodwin, Smith and Hammond (2000). While the use of aggregate data may not fully capture the heterogeneity that exists at the farm level or capture the complexity of the underlying physical processes, it is useful when trying to draw general conclusions concerning the impact of agricultural policies on environmental outcomes. The last approach is the one employed in this study.

An example of a study that integrated a physical and economic modeling framework is found in Wu et al. (1996). They explored the impact of farm commodity programs on nitrate water pollution in the high plains area that stretches from northern Texas to southern Wyoming and Nebraska. They included two policy variables - Acreage Reduction Program (ARP) rates and target prices - into acreage response equations for wheat, sorghum, cotton, and alfalfa. While changes in input use also affect nitrate runoff and leaching, this study looked only at the impact of changes in crop mix. They employed information from the 1987 NRI to develop distributions of each crop by soil type, irrigation system, and cropping practice for each county (i.e., the unit of observation). The EPIC-PST crop growth-chemical transport model was then combined with the crop distribution data to estimate nitrogen losses due to potential runoff and leaching associated with various combinations of soil type and cropping activity.[5] Using the acreage response equations, they predicted changes in crop mix due to the availability of government support payments. If the crop mix shifted toward soil types and cropping activities that exhibited greater runoff and leaching potential, they concluded that nitrate water pollution would increase.

Results from the entire sample indicated that an increase in the target price for corn

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[5] An extensive description of the EPIC simulation model can be found in Williams, Jones and Dyke (1984).

and sorghum increased nitrogen runoff and leaching, while an increase in the target price for wheat and cotton would have the opposite effect. The difference could be explained by noting that corn and sorghum require more fertilizer and irrigation than wheat and cotton. When the high plains region was subdivided into 12 subregions, the previous results did not hold for all subregions. Elasticities of nitrogen runoff and leaching with respect to target prices for corn, sorghum, and wheat varied from -0.05 for wheat in the Central High Plains of Kansas to 0.13 for corn in Southern High Plains of Texas. Elasticities with respect to cotton were substantially larger in magnitude, ranging from -0.05 to -0.51. Results for ARP rates also indicated that the impact on nitrate runoff and leaching varied by subregion. Elasticities of nitrogen leaching and runoff for all crops varied from -0.31 in the Southern High Plains of Texas to 0.08 in the Northern High Plains of Nebraska. The elasticities were significant, but small in magnitude in all cases except cotton. While policies that shift production into cotton lead to lower rates of nitrate water pollution, the crop mix changes associated with these government policies, in general, did not lead to large changes in nitrate water pollution.

One of the most comprehensive studies of the interaction between government agricultural policies and measures of environmental quality, i.e., groundwater pollution, can be found in Wu and Segerson (1995). Their study contains detailed site characteristic data that is often missing in other studies. Specifically, they looked at the impact of three policies - Acreage Reduction Program (ARP) for corn, the corn target price, and a tax on agricultural chemicals - on “potential” groundwater pollution in Wisconsin. Using county-level data, they estimated crop share equations for 6 major crops. They included ARP rates, corn target prices, detailed input prices, and extensive land characteristics, including soil texture classifications, land capability class, rainfall and temperature, and land slope. The estimated acreage elasticities demonstrated the importance of site characteristics. Of the 54 estimated acreage elasticities with respect to site characteristics, 40 were significant at the 1% level.

After estimating acreage elasticities, they simulated the impact of changes in the policies under study on changes in the acreage of the 6 crops from their 1990 levels.[6] Since actual groundwater pollution data were not available, they estimated the impact on “potential” groundwater pollution by determining the amount of acreage that was vulnerable

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[6] They simulated the necessary changes in the policy to induce a 1% reduction in high-polluting acreage. For example, this would require a 2.3% reduction in the target price for corn.

to pollution and used to grow a polluting crop. The vulnerable acreage designation was a function of site characteristics, while the polluting crop designation was a function of the chemical requirements of the crop in question. Specifically, they assumed that only land that was vulnerable and used to grow a polluting crop would lead to potential groundwater pollution, and thus designated as high-polluting land. Therefore, policy-induced changes in crop mix that led to increases in the production of more chemically-intensive crops on more vulnerable land would potentially lead to more groundwater pollution.[7]

The major findings from their study include the following: (1) the impact on potential groundwater pollution varied by policy, (2) the effects of each policy varied by region, and (3) the inclusion of detailed site characteristics is essential when evaluating the impact of government policies on the environment. They found that decreases in corn target prices, increases in ARP rates, and increases in chemical tax rates reduced high-polluting acreage, but increased low-polluting acreage.[8] The overall impact was ambiguous since empirical estimates of the level of groundwater pollution associated with low and high-polluting acreage were not available. In general, they concluded that a reduction in ARP rates reduced high-polluting acreage with less impact on total acreage than the other two policies. While regional impacts varied, they found that the impact of chemical taxes was less variable by region than the other two policies. Finally, they compared reductions in high-polluting acreage by region to the demand for groundwater quality as proxied by the total and per capita groundwater withdrawals. They found that reductions in the ARP rates reduced high-polluting land in regions where the demand for water quality was the highest, while the other two policies were not as well targeted.

Also using county data from Wisconsin, Plantinga (1996) looked at the impact of milk price supports on land use shares, where land could either be allocated to agriculture (milk production) or to forest (timber production). Modeling the decision as a function of net returns to each use, he estimated the probability that land was used for milk or timber production. After separating the land into 4 classes based on the USDA land capability classification system, Plantinga estimated the impact of altering milk price supports on the allocation of land by land class. He then used soil erosion rates from the 1982 NRI by land

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[7] Since there was no way to determine which plot of land came into production for each crop, they assumed that changes in acreage were uniformly distributed across land with different leaching potential.

[8] Decreases in corn target prices encourage farmers to reduce the amount of land devoted to corn production. Since corn is considered to be a "high-polluting" crop due to cultivation and chemical input requirements, this would lead to a reduction in potential pollution (Wu and Segerson 1995).

capability class to draw inferences about the impact of changes in milk price supports on soil erosion and water quality. For example, a reduction in milk price supports shifted low quality land into forest. Since soil erosion rates were higher for high land capability classes (i.e., low quality land) and forest use entails less land-damaging management, the expansion of forest (or reduction in agricultural land) induced by the reduction in price supports led to a reduction in soil erosion and a potential gain in water quality.

Using a more direct approach, Goodwin and Smith (2003) estimated soil erosion within a system of equations designed to capture the interactions of production choices and environmental impacts. Using county-level panel data, they used 2-stage least squares to estimate a system of equations for crop insurance participation, CRP participation, fertilizer and chemical use, conservation effort, and soil erosion.[9] While Goodwin and Smith included measures of land quality, i.e., the K-factor and T-factor, in their CRP participation, conservation effort, and fertilizer use equations, they did not attempt to model site characteristics to the degree found in Wu and Segerson (1995).

In their soil erosion equation, they found that insurance participation was negatively related to soil erosion, though a 1% increase in participation implied only a 0.02 ton per acre reduction in soil erosion. Disaster payments had no significant impact on soil erosion, while, as expected, increases in CRP participation implied significant decreases in soil erosion. Government program payments, defined as the ratio of government payments received to total gross farm income, exhibited a significant positive impact on soil erosion. In this case, a 1% increase in government payments implied a 0.135 ton per acre increase in soil erosion. Finally, increases in conservation effort, proxied by the P-factor in the NRI, led to a significant reduction in the level of soil erosion. While the impact of federally-subsidized crop insurance on soil erosion was minimal (contrary to many expressed concerns), their results suggested that other government agricultural payments may exacerbate soil erosion problems. They concluded that approximately 50% of the reductions in soil loss due to the CRP were eliminated by increases in response to the provision of other agricultural payments. Since they employed an aggregate government payment measure, it is not possible to determine if different program payments exhibited a differential impact with respect to soil erosion.

In a similar vein, Wu (1999) estimated a simultaneous system of equations for

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[9] Crop insurance participation was defined as the ratio of net insured acres to total planted acres, and CRP participation was defined as the percentage of total agricultural acres enrolled in the CRP.

corn insurance participation and crop shares for corn, soybeans, hay, and pasture using Area Studies data from the Central Nebraska Basin. In contrast to Goodwin and Smith (2003) and Goodwin et al. (2000), Wu used farm level data that linked production activities to site-specific environmental data collected in the NRI. After matching farmland locations to NRI sites, interviews were conducted with farmers to collect information on farming practices, insurance participation, and personal characteristics. While this approach avoids the issues associated with aggregation, the results are location-specific and may not be valid outside the limited area of study.

He found that farmers who purchased corn insurance shifted land allocation from hay and pasture to corn and soybeans. The shifting of land to the production of corn diminished with increases in farm size. For example, the corn crop share increased by 27% for the small farm classification, while it increased by only 5% for the large farm classification.[10] In all size classifications, the crop share for hay and pasture increased from 3% to 12%. Since corn uses larger amounts of nitrogen and pesticides than hay and pasture, the shift created greater opportunities for water contamination. Using USDA estimates for chemical application rates in the study area, Wu argued that the increase in chemical use associated with the expansion of corn production exceeded any possible reduction in chemical use associated with the risk reduction properties of crop insurance. As a result, he argued that the provision of crop insurance would lead to greater levels of groundwater contamination.

Also using Area Studies data for the Central Nebraska Basin, Wu and Babcock (1998) employed a multinomial logit model to explore the relationship between management practices and crop yield, input use, and soil erosion. They estimated a series of equations for crop yield, input use, and soil erosion for eight management practice combinations under study. The soil erosion equations contained a number of regressors - T-factor, pH levels, land capability class, slope of field, and average water capacity among others - to incorporate biological, chemical, and physical soil characteristics. The slope of the field was the only regressor found to be significant in more than 2 of the 8 management practice models.[11] In addition, the soil erosion equation in each model included a dummy variable for crop

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[10] Wu hypothesized that small farms are more risk averse so they are more sensitive to the risk reduction provided by crop insurance.

[11] This result is not surprising since they used the Universal Soil Loss Equation (USLE) from the NRI as their measure of soil erosion. The USLE contains a factor representing the slope of the field, so the impact of the slope was contained in both the dependent and independent variables.

insurance as a regressor. The crop insurance coefficient estimates in each model were all positive, but none were statistically significant at the 10% level.

In summary, very little research has been conducted that makes the connection between agricultural policies, e.g., crop insurance and agricultural price supports, and measures of environmental quality. Even those studies that attempted to incorporate the impact of government agricultural policies in models of soil erosion failed to take into account the myriad of programs available to the farmer. For those that included some measure of aggregate government payments (Goodwin and Smith (2003)), they did not account for the possibility that different payment schemes may induce different changes in soil erosion. Instead of directly incorporating these programs in the model, most of the research associates increases in chemical use and expansions of acreage or changes in crop mix that favor chemically-intensive crops with higher levels of soil erosion and other detrimental changes in the environment.

In addition, most of the research has concentrated on changes in water quality, while few (Goodwin and Smith (2003) and Goodwin et al. (2000) are exceptions) have addressed the impact of agricultural policies on levels of soil erosion. At the same time, few studies (with Wu and Segerson (1995) and Wu and Babcock (1998) being exceptions) have attempted to incorporate extensive site characteristics in the economic or physical components of the modeling framework. All of the studies, taken in combination, have drawn inconclusive results concerning the impact of agricultural policies on measures of environmental quality. In almost all cases, the effect was found to vary by crop and geographic location.

4.3 Methodology

4.3.1 Soil Erosion Measure

To undertake this study, it is necessary to provide an empirically implementable definition of soil erosion. Soil erosion is defined as the detachment and transportation of soil particles by wind or water activity (Larson et al. 1983). While exact measures of soil erosion are difficult to obtain, the Universal Soil Loss Equation (USLE) has been employed frequently (see Amos and Timmons (1983) and Goodwin and Smith (2003)) to proxy for soil erosion. The USLE was designed to predict long-term average annual soil loss occurring from sheet and rill erosion on specific lands where specific management and cropping practices were employed. The USLE equation is $A = RKLSCP$, where A is predicted annual soil loss, K is an inherent soil erodibility factor, R is a rainfall erosivity factor, L is a slope-length factor, S is a slope-steepness factor, C is a cropping management factor, and P is a factor to incorporate erosion control practices.

The K factor value for a particular soil type is determined from an equation that includes the following variables: silt percent, sand percent, organic matter content, structure (e.g., fine granular soil), and permeability . The K factor is assumed to be constant for each soil type, regardless of the production practices undertaken on the soil or the climatic differences associated with the geographic location of the soil. The rainfall erosivity factor R accounts for the soil erosivity associated with the impact of rain drops on the soil and the resulting runoff associated with the impact. It is a function of the kinetic energy associated with the rain drop impact and the maximum 30 minute intensity of the rainfall. The cropping management factor C is determined as the ratio of soil loss from a specific cropping practice to the soil loss from soil in a tilled, continuously fallow condition. Among other management activities, this incorporates the effects of crop cover, crop rotation, and tillage systems. The supporting practices factor P accounts for the impact of erosion control practices, and is constructed as the ratio of the soil loss associated with a particular erosion control practice to the soil loss using an "up-and-down" hill cropping practice. Among other things, this factor accounts for different contour plowing and terracing methods (Mitchell and Bubenzer 1980).

4.3.2 Model

Water-induced soil erosion is a dynamic and complex process driven by the interaction of physical, chemical, biological, climatic, and economic factors. Although the process is complex, the level of soil erosion is primarily determined by soil characteristics (e.g., the slope and permeability of the land), climate (e.g., the frequency and intensity of rainfall), land use (e.g., cropland vs. pastureland), cropping practices (e.g., tillage and crop rotation), and conservation practices (e.g., cover and terracing). While the soil characteristics and climate factors are exogenous to the farmer, the choice of land use, cropping practice, and conservation practice are a function of the social and economic factors.[12]

For example, the choice of how to use the land is determined by the returns to the alternative uses of the land. Assuming land meets the eligibility requirements for enrollment in the Conservation Reserve Program, whether or not the land is actually enrolled will depend on the returns to enrollment, which are primarily a function of the rental rate and cost-share arrangements, versus the returns to the best alternative use of the land, such as crop production.[13] The expected returns to crop production are a function of the expected price and yield (which are not known with certainty at the time the land allocation decision is made), the costs of production, and the agricultural price (income) support payments available to the farmer. In addition, the variability of expected returns may be affected by the risk management tools that are made available to the farmer. The choices of cropping and conservation practices are also a function of economic variables. For example, the adoption of conservation tillage, which reduces soil erosion, has been shown to be a function, among other things, of farm size and off-farm employment (Fuglie 1999).

While the inherent erodibility of the soil places some boundaries on potential soil erosion, the activities undertaken on the land drive changes in the level of soil erosion over time. The basic belief behind most of our conservation programs is that cultivated cropland is more susceptible to increases in soil erosion than lands which are noncultivated or used as forest, range, or pasture. Disregarding the impact of government support programs, the use of the land will depend on the market returns to the alternative uses. To capture the impact of the expected market returns to crop production, we included a three-year county-level average of real net returns per harvested acre for corn, soybeans, and winter wheat in our model. We constructed the revenue for each crop by multiplying the harvested yield by the state-level market price taken from the NASS online database. The price was constructed as the average of the monthly state prices for the most active harvest months for each crop.[14]

The net return variable was constructed by subtracting the average total production cost per acre from the revenue for each crop. The total crop production costs were

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[12] These choice variables are also a function of climate and land characteristics. For example, the land use decision is constrained by the ability of the soil to support the production of a given crop in an economically viable manner.

[13] Since CRP land is under contract for ten to fifteen year periods, the option value of the land may also be a significant consideration when deciding whether or not enroll land in the CRP. While an important concern, this is beyond the scope of the present study.

[14] The information concerning the most active harvest months for each crop were taken from the "Usual Planting and Harvesting Dates for U.S. Field Crops" section of the NASS Agricultural Handbook No. 628.

obtained from the USDA/ERS Commodity Costs and Returns data. The production data were estimated for each crop and USDA farm resource region on an annual basis. The nominal net return variable was inflated to 2001 terms using the producer price index. We divided the net return for each crop by the total harvested acres for that crop to construct the net return per acre. Finally, the expected county-level net returns per acre for each crop were calculated as a 3 year average of net returns as previously constructed.

In addition to market returns, the availability of government income support and risk management programs provide incentives for farmers to adjust land usage, at least at the margin. Payments that are directly tied to production (target price-based and loan deficiency payments) provide incentives for farmers to expand acreage and/or crop existing acreage more intensively. On the other hand, payments that are not tied to current production (AMTA payments) or those delivered on an ad hoc basis (disaster payments) may provide farmers with little incentive to alter production.[15] Hennessy (1998) has argued that decoupled payments may affect crop acreage by encouraging producers to accept more risk as their wealth increases or by reducing financial constraints that limit their acceptance of more risk.[16] In addition, the frequency of ad hoc assistance may encourage farmers to incorporate those payments into expectations of future income and thus encourage them to accept greater risk. In addition to the risk management and income support programs, the federal government has provided payments (e.g., Conservation Reserve Program (CRP) rental income) to encourage the removal of highly erodible land from production.[17] If correctly targeted, these payments should lead to a reduction in soil erosion.

The impact of these various programs on production choices (and thus soil erosion) is primarily an empirical question. To capture the impact of these various agricultural programs on soil erosion, we included the following categories of agricultural payments in our model: (1) target price-based deficiency payments, (2) AMTA payments, (3) loan

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[15] AMTA payments were authorized by Congress in the FAIR Act of 1996 to replace government support payments tied to current production and prices. Farmers were eligible to receive AMTA payments if they enrolled acreage in annual farm programs in any year from 1991 to 1995. These fixed payments, which were intended to decline and finally terminate at the end of the FAIR Act in 2002, were based on historical program benefits (which were based on historical production) and therefore not linked to current production.

[16] Hennessy's argument assumes that economic agents exhibit declining absolute or relative risk aversion (DARA or DRRA) preferences. Even with DARA or DRRA preferences, his results indicate that the effect is likely to be small, though statistically significant.

[17] The level of CRP payments received are a function of a bidding process whereby landowners submit bids on land that meet certain requirements, such as being assigned an erodibility index value of 8 or higher. These bids are accepted or rejected within the context of the program land retirement goals. In addition to CRP rental rates, our conservation payments data include, among other things, CRP cost-share payments and water conservation payments.

deficiency payments, (4) disaster payments, and (5) conservation payments. All of these payments are a 3 year average of county-level real payments per farm acre.

Many people have also expressed concerns about the impact of the provision of federally-subsidized crop insurance on crop mix, planted acreage, and input use. As demonstrated in Chapter 3, federally-subsidized crop insurance provides incentives for farmers to alter land allocation and input use. If those changes bring more erodible land into production, encourage the implementation of more intensive cropping practices, or discourage the adoption of conservation practices, they are likely to contribute to higher levels of soil erosion. To capture the impact of federally-subsidized crop insurance on soil erosion, we included a 3 year average of the percentage of planted acres in the county that are insured for each crop in our soil erosion equation.

Although we used a reduced-form approach with respect to modeling the impact of government payments on crop acreage, cropping practice, and conservation practices due to the lack of crop-specific payments data, we modeled insurance participation as an endogenous variable by modeling the determinants of insurance purchases within a 2 stage least squares framework. This approach was chosen since the impact of government payments on soil erosion should be directly attributable to their impact on crop acreage, cropping practice, or conservation practice (even though disentangling the individual effects may be difficult), while the impact of government payments (i.e., premium rate subsidies) with respect to crop insurance affect soil erosion through their impact on insurance purchases, which may then impact the other choice variables.

In our model of crop insurance demand, we included the producer-paid portion of the insurance premium rate and the loss ratio (a proxy for expected indemnity payments). We hypothesize that an increase in the premium rate will reduce crop insurance participation (as measured by the ratio of insured acres to total planted acres) and will decrease acreage in the planted crop. If that crop is associated with higher levels of erosion, the increase in the premium rate should reduce the level of soil erosion. We hypothesize the opposite effect for the loss ratio. An increase in the loss ratio should increase insurance participation and crop acreage. If that crop is associated with higher levels of erosion, the increase in the loss ratio should increase the level of soil erosion. There is also evidence that agents exhibit a differential response to premium rates when facing different expected indemnity payments (Goodwin 1993). Specifically, farmers who expect to receive larger indemnity payments are less responsive to increases in premium rates. To capture this differential response, we included an interaction term of the premium rate and loss ratio.

For given premium rates and indemnity payments, risk-averse farmers should also exhibit a higher demand for insurance if they face a higher yield risk. To capture the yield risk faced by the producer, we also included the coefficient of variation of county average yields. The productive capacity of the land may also have an impact on insurance demand. Land with high productivity may reduce the likelihood of a yield shortfall, but may also increase the magnitude of the loss in the event of crop failure. To capture land productivity, we included the county average water holding capacity, a primary constraint on agricultural productivity. Although no consensus has been reached in the empirical literature, crop insurance may act as a substitute for other inputs, such as fertilizers, in the production process. To capture the impact of fertilizer use on crop insurance demand, we included a three-year average of county-level fertilizer/chemical expenditures.[18] To capture possible borrowing constraints facing the farmer, we included a 5 year average of lagged county net farm income. We hypothesize that a lower net income stream would encourage borrowing, and therefore increase the likelihood of the borrower facing insurance purchase requirements set by the lender. Finally, large farms may be more likely to purchase insurance since, among other things, they provide higher commission payments that encourage more intensive marketing by insurance agents. We include county average farm size (in acres) to capture this effect.

In addition to market returns, government program payments, and crop insurance, other factors may affect soil erosion through their impact on acreage allocation and the adoption of cropping/conservation practices. Since cropping activities, such as plowing, are major contributing factors to soil erosion, land that remains in pasture, range, or forest should exhibit lower levels of soil erosion than land under cultivation. The soil erosion measure (USLE) is reported in the NRI only on land that is designated as cropland, pastureland, or CRP land. The previously discussed variables are included to capture the impact of cropland and CRP use, but modeling pasture use is more complicated since pasture can be used for a number of activities, such as grazing and hay production. Given the data limitations, particularly with respect to the derivation of pasture costs, we chose to forego constructing a net return variable for pasture use.[19] To capture the impact of

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[18] A limitation with respect to our expenditure data should be noted. Our data are county-level expenditures and are not crop-specific. Therefore, we cannot take into account different application rates across different crops.

[19] Using estimated pasture yields from the soils interpretation database, Lubowski (2002) constructed a

pasture use on soil erosion, we used a 5 year lag of the ratio of pasture acres to the sum of crop, pasture, and CRP acres.

If government program payments and crop insurance encourage farmers to bring economically marginal land into production, this may include land that is more steeply sloped or more inherently erodible than land already in production. This land may require more intensive cultivation than land already in production. As a result, government programs may affect our measure of soil erosion by affecting the distribution of the K (inherent erodibility), L (slope length), and S (slope steepness) factors of land under cultivation. Even if identical cropping practices are used for land already in production and this new land being brought into production, the new land would be more likely to contribute to erosion because of its physical characteristics. While bringing new land into cultivation may alter the distribution of the K, L, and S components of the USLE, it is unlikely that government programs could affect the rainfall erosivity factor (R) since this is likely not to vary within close geographic proximity (e.g., land within a county). Since it is unlikely that government policy can affect the R factor, we condition this out in our soil erosion estimation equation.

Therefore, our soil erosion estimation equation can be summarized as follows:

$$\begin{aligned} USLE = \; & \sum_{i=1}^{3} b_i \cdot MKTRET_i + b_4 \cdot DISASTER + b_5 \cdot LDP \\ & + b_6 \cdot DEFICIENCY + b_7 \cdot CONSERVE \\ & + b_8 \cdot CONSERVE * EI + b_9 \cdot LAGPAST + b_{10} \cdot RFACT \\ & + \sum_{i=11}^{13} b_i \cdot INSURE_i + \epsilon \end{aligned} \tag{4.1}$$

where $USLE$ is the measure of water-induced soil erosion measured in tons/acre/year, $MKTRET_i$ is the market return to crop i, $DISASTER$ is the county average real disaster payments per farm acre, $DEFICIENCY$ is the county average real deficiency payments per farm acre, LDP is the county average real loan deficiency payments per farm acre, $CONSERVE$ is the county average real conservation payments per farm acre, $CONSERVE * EI$ is an interaction term of conservation payments and the soil erodibility index, $LAGPAST$ is the 5 year average of the lagged percentage of pasture acreage, $RFACT$ is the rainfall factor from the USLE, $INSURE_i$ is the percentage of crop acres insured for crop i, and ϵ is an error term. Deficiency payments were not available after 1996 and are not included in the 1997 model. AMTA payments were not available before 1996, and were not included in the 1992 model.

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net return to pasture use in a land use transition model.

There is a crop insurance demand equation for each of the three crops in our model. The general form of each equation can be summarized as follows:

$$\begin{aligned} INSPART = \; & b_0 + b_1 \cdot PREM + b_2 \cdot LR + b_3 \cdot PREM * LR + \\ & b_4 \cdot CVYLD + b_5 \cdot FMACRES + b_6 \cdot NETINCOME + \\ & b_7 \cdot AWC + b_8 \cdot CHEMEX + \epsilon \end{aligned} \qquad (4.2)$$

where $INSPART$ is the percentage of planted acres that are insured, $PREM$ is the producer-paid premium rate, LR is the loss ratio, $PREM * LR$ is an interaction term conditioning the impact of the premium rate on the loss ratio, $CVYLD$ is the coefficient of variation of mean yield, $FMACRES$ is the county average farm size (in acres), $NETINCOME$ is a 5 year average of lagged net farm income, AWC is the county average water holding capacity, $CHEMEX$ is the county average fertilizer/chemical expenditures, and ϵ is an error term.

4.3.3 Data

Our sample consists of counties where corn, soybeans, and winter wheat account for more than 90% of harvested acres in the county.[20] In addition, we exclude any counties that meet this criteria but fail to produce all three crops. This results in a sample of 778 counties in 1992 and 773 counties in 1997. Figure 4.1 provides a map of the counties contained in our 1992 sample.[21] Our sample consists of counties from the upper Midwest states (e.g., Illinois and Ohio), the mid-Atlantic states (e.g., Virginia and Maryland), the northern sections of the Southeastern states (e.g., North Carolina and Tennessee) and the lower Plains states (e.g., Nebraska and Kansas). Excluding the Mississippi Portal region which is not well represented in our sample, we include most of the areas that have exhibited the highest levels of sheet and rill erosion and are of major concern.

Table 4.1 contains the means and standard deviations of sheet and rill erosion by state in our sample for the 1992 and 1997 periods. In addition, the table contains the number of counties (N) from each state in our sample. Illinois, Indiana, Iowa, Missouri, Kansas, and Ohio generally contain the largest number of counties, while Arkansas, Louisiana, Delaware, and Minnesota generally contain the fewest number of counties contained in our sample.

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[20] Total harvested acreage includes acreage devoted to the production of corn, soybeans, winter wheat, durum wheat, other spring wheat, grain sorghum, upland cotton, rye, barley, oats, peanuts, and rice.

[21] A map for the 1997 sample period is not included since most of the counties appear in both samples.

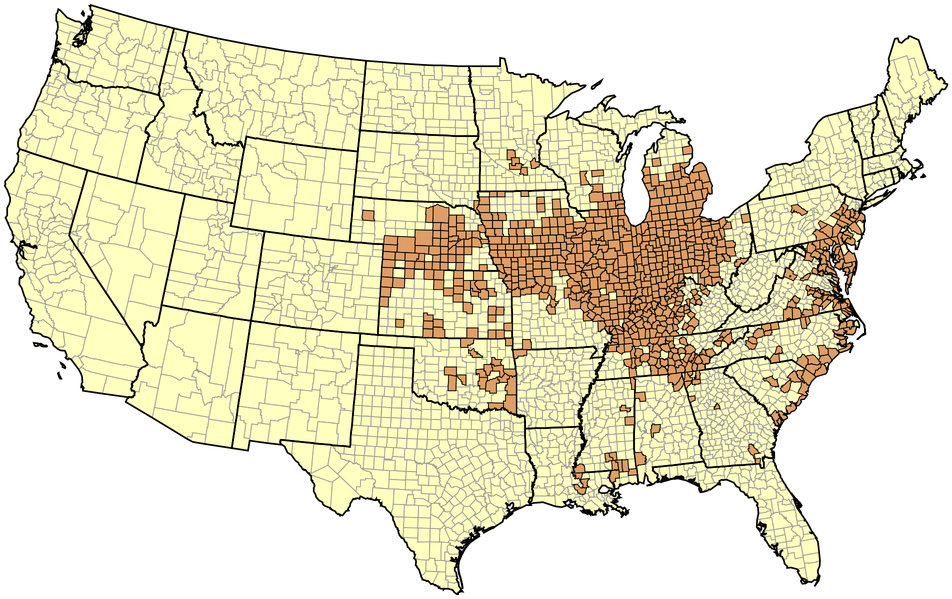

Figure 4.1: Sample Counties (1992)

Texas contained no counties that met our criteria in 1992, but contained nine counties that did in 1997, while Minnesota had five counties that met the criteria in 1992 but none that did in 1997. In 1992 the mean soil erosion rate for our entire sample was 3.3113, though the rates ranged from a high of 5.7792 in South Dakota to a low of 1.7901 in Oklahoma. The mean soil erosion rate declined to 2.8000 by 1997 for our sample, though a few states (Illinois, Iowa, Maryland, and Pennsylvania) still exhibited sheet and rill erosion rates in excess of 3.5 tons/acre/year.

This study makes use of data collected from a number of sources. In particular, we make extensive use of 1992 and 1997 NRI data (see chapter 1 for a general discussion of the NRI). Among other things, the measure of sheet and rill erosion ($USLE$) is contained in the NRI data. The crop yield and price data are taken from the National Agricultural Statistics Service (NASS) online database, while the production cost data are contained in the Economic Research Service (ERS) Commodity Cost and Returns database. County-level

Table 4.1: Sample County Soil Erosion Rates by State

State	*1992*			*1997*		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Alabama	5	2.7396	1.1348	7	1.9577	0.2935
Arkansas	1	1.0817	···	1	1.8103	···
Delaware	2	2.2437	1.8115	2	1.9166	1.4265
Georgia	8	1.2405	0.7505	2	1.6937	0.9004
Illinois	98	4.1906	1.6984	87	3.8175	1.6230
Indiana	92	2.9948	1.1574	88	2.6401	0.9910
Iowa	64	4.9747	2.4079	53	4.1609	1.9941
Kansas	37	2.5433	2.0995	53	1.9640	1.1514
Kentucky	63	3.3180	1.3258	54	2.5412	1.0476
Louisiana	3	1.8943	1.8040	3	2.8611	0.9552
Maryland	20	4.4983	3.1220	20	3.9254	2.9554
Michigan	45	1.6582	0.9832	39	1.4395	0.8289
Minnesota	5	2.8327	1.0263	0	···	···
Mississippi	11	2.3828	1.0289	7	3.1334	1.7526
Missouri	53	4.6949	2.1127	69	3.3194	1.6631
Nebraska	49	2.7397	1.7806	42	2.5035	1.4937
New Jersey	10	3.9930	2.1733	10	3.4422	1.7489
North Carolina	26	3.8058	3.1497	25	3.1025	2.7826
Ohio	59	2.8347	1.1666	67	2.2428	0.9281
Oklahoma	17	1.7901	0.9404	15	1.3702	0.7036
Pennsylvania	9	4.9151	1.6169	18	4.0701	1.3056
South Carolina	9	1.8373	0.7976	6	1.6346	0.9739
South Dakota	1	5.7792	···	13	2.1483	1.0032
Tennessee	51	1.9825	1.3135	39	1.6465	1.3105
Texas	0	···	···	1	0.5833	···
Virginia	29	3.5414	1.8867	35	3.0231	1.2340
Wisconsin	11	3.5062	0.9917	17	3.0318	1.3281
Total	778	3.3113	1.9983	773	2.8000	1.6605

Commodity Credit Corporation (CCC) payment data from the 1990-1998 period are taken from unpublished USDA-FSA sources. Crop insurance program data are taken from the RMA's unpublished county level "summary of business" database. Farm acreage data were taken from the Census of Agriculture. County-level mean average water holding capacity (AWC) was constructed from data included in the SOILS-5 database. All nominal economic variables are inflated to 2001 terms using the producer price index. A list of variables and summary statistics for the 1992 model can be found in Table A.27, while a list of variables and summary statistics for the 1997 model can be found in Table A.28.

4.4 Results

Table 4.2 presents the results from our 2SLS estimation of the 1992 model specification. In our soil erosion estimation equation, the 3 year average (1991-1993) of net market returns for corn are positively and significantly associated with higher levels of soil erosion, though higher net market returns for soybeans are not significantly associated with higher levels of soil erosion. Counties that experience higher net market returns for winter wheat exhibit significantly lower levels of soil erosion. A priori expectations are that row crops (for example, corn and soybeans) should be associated with higher levels of soil erosion than small grain crops (for example, winter wheat). If higher net market returns lead to higher planted acreage, our results support the a priori expectation that the returns to planting corn/soybeans will be associated with higher levels of soil erosion, while winter wheat returns will be associated with lower soil erosion.[22]

The focal point of our analysis is the impact of government program payments and crop insurance on soil erosion. The coefficient estimates on loan deficiency payments and deficiency payments are insignificant at the 10% level. While deficiency payments were not provided for soybean production, corn and winter wheat were program crops that were eligible to receive deficiency payments.[23] The overall insignificant impact of these support payments may indicate the offsetting effects of incentives to increase production in response to the reduction in risk and conservation compliance requirements associated with the receipt of government program payments.[24] Since disaster payments are received after production decisions (e.g., crop mix and cultivation practice) are made, it is somewhat surprising that they exhibit a significant positive impact on soil erosion.[25]

An increase in conservation payments is associated with a decrease in soil erosion. This provides support to the argument that conservation payments that encourage farmers to remove erodible land from production and to adopt conservation practices are an effective

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[22] The Pearson correlation coefficient between corn and soybean net market returns is 0.72, so a potential collinearity problem exists and identification of the separate effects may be difficult.

[23] We also estimated a model using total government payments (excluding conservation payments) and found that total payments exhibited no statistically significant impact on soil erosion.

[24] We also estimated two alternative versions of our model, conditioning out the cropping and management practices in one model and the physical characteristics, such as slope and inherent erodibility, in the other model. While the overall effect of deficiency payments is insignificant, they exhibit a statistically significant impact on cropping and conservation practices, controlling for the physical characteristics of the land, but exhibit no impact on the the distribution of the physical characteristics.

[25] Though significant, the magnitude of the change is very small. A doubling of disaster payments from its mean value of $1.50 per farm acre would lead to a 4% increase in the level of soil erosion from its mean value of 3.3113.

tool to reduce soil erosion. The interaction term indicates that conservation payments exhibit a differential impact on soil erosion given different levels of soil erodibility. Without the inclusion of the interaction term, conservation payments exhibit a significant positive impact on soil erosion. Without controlling for differences in soil erodibility, this should not be surprising since conservation payments, if correctly targeted, are higher on more highly erodible land (i.e., land that is most likely to experience soil erosion).

Given that land used as pasture requires little (or no) cultivation, we would expect to find that the higher the lagged percentage of land used as pasture, the lower the level of soil erosion. This is consistent with our findings. As expected, the rainfall erosivity factor is associated with higher levels of soil erosion. The predicted values for corn insurance participation from our 2SLS estimation are associated with higher levels of soil erosion, while wheat insurance participation is associated with lower levels of soil erosion. Both coefficient estimates are significant at the 10% level, while soybean insurance participation exhibits no significant impact on soil erosion. Assuming that higher insurance participation is associated with higher planted acreage, our results support our findings with respect to net market returns as to the impact of row crops (at least in the case of corn) and small grains (winter wheat) on soil erosion.

The results from the 2SLS estimation of insurance participation generally confirm a priori expectations. The producer-paid portion of the crop insurance premium rate is negatively associated with insurance participation for corn and soybeans, though is not significantly associated with wheat insurance participation. The loss ratio is positively related to corn and wheat insurance participation, while the coefficient of variation of mean yield is positively associated with insurance participation for all three crops. The coefficient estimates on the interaction term indicate that the producers of all three crops exhibit a differential response to premium rate increases if those increases are conditioned on the expected indemnity payments (i.e., loss ratios). Producers who receive higher indemnity payments are less responsive to increases in premium rates. Land quality, as proxied by county average water holding capacity, is associated with significantly higher corn and soybean insurance participation. This may indicate that producers are more willing to insure more productive land since any systematic crop failure will be associated with higher levels of foregone production. In all three cases, larger farms (in acreage terms) are associated with higher levels of insurance participation, while chemical expenditures and lagged net farm income are negatively associated with insurance participation. In particular, this

Table 4.2: 2SLS Results - Soil Erosion Estimates (1992)

Variable	Soil Erosion	Corn Insurance	Soybean Insurance	Wheat Insurance
Intercept	1.6840*	−0.2223*	−0.1331*	0.0821
	(0.5331)	(0.0733)	(0.0735)	(0.0520)
Corn Returns	0.0097			
	(0.0043)			
Soybean Returns	0.0032*			
	(0.0048)			
Wheat Returns	−0.0110*			
	(0.0026)			
Disaster	0.1015*			
	(0.0535)			
Loan Deficiency	−0.9277			
	(0.5790)			
Deficiency	−0.0037			
	(0.0208)			
Conservation	−0.1804*			
	(0.0410)			
Conservation*EI	0.0221*			
	(0.0031)			
R Factor	0.0045*			
	(0.0021)			
Corn Insurance	5.1402*			
	(1.8753)			
Soybean Insurance	−1.1679			
	(2.4014)			
Wheat Insurance	−5.8505*			
	(1.8271)			
Lagged Pasture	−1.7518*			
	(0.9910)			
Premium		−1.4327*	−0.7698*	−0.3718
		(0.4029)	(0.2225)	(0.2318)
Loss Ratio (LR)		0.0206*	0.0008	0.0101*
		(0.0064)	(0.0078)	(0.0026)
Premium*LR		0.4271*	0.4974*	0.0968*
		(0.1053)	(0.1020)	(0.0386)
CV Yield		0.0051*	0.0062*	0.0011*
		(0.0009)	(0.0013)	(0.0006)
AWC		1.7950*	1.0775*	−0.4979
		(0.3970)	(0.3920)	(0.3334)
Farm Acres		0.0553*	0.0503*	0.0418*
		(0.0081)	(0.0082)	(0.0066)
Fertilizer		−0.3059*	−0.3354*	−0.2234*
		(0.1569)	(0.1506)	(0.1239)
Lagged Income		−0.0357*	−0.0317*	−0.0175*
		(0.0107)	(0.0106)	(0.0082)

The standard errors of the coefficients estimates are in parentheses.

The asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

indicates that lower net income from the preceding 5 year period is associated with higher insurance purchases. This may reflect insurance purchase requirements imposed by lenders if producers find it necessary to borrow funds to supplement the lower net income.

Table 4.3 presents the results from our 2SLS estimation of the 1997 model specification. In our soil erosion estimation equation, the 3 year average (1996-1998) of net market returns for all three crops are not significantly associated with soil erosion. These results are inconsistent with the results from the earlier period that indicate that the production of row crops (at least corn) is associated with higher levels of soil erosion, while small grain (e.g., winter wheat) production is associated with lower levels of soil erosion. This is somewhat surprising since the elimination of planting restrictions in 1996 should elevate the importance of market returns to the producer's production decisions.

The coefficient estimates on disaster payments and AMTA payments are insignificant at the 10% level.[26] Since AMTA payments are not tied to current production decisions, it is not surprising that they do not exhibit a significant impact on soil erosion.[27] Consistent with the results from the earlier period, loan deficiency payments exhibit no significant impact on soil erosion. Unlike the results from the earlier period, disaster payments are not associated with higher levels of soil erosion.[28]

As in the 1992 specification, an increase in conservation payments is associated with a decrease in soil erosion. This provides support to the argument that conservation payments that encourage farmers to remove erodible land from production and to adopt conservation practices are an effective tool to reduce soil erosion. The interaction term indicates that conservation payments exhibit a differential impact on soil erosion given different levels of soil erodibility. Without the inclusion of the interaction term, conservation payments exhibit a significant positive impact on soil erosion.

As in the previous period, we found that the lagged pasture variable is associated with lower levels of soil erosion, and the rainfall erosivity factor is associated with higher levels of soil erosion. As in the 1992 specification, the predicted values for corn insurance

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[26] We also estimated two alternative versions of our model, conditioning out the cropping and management practices in one model and the physical characteristics, such as slope and inherent erodibility, in the other model. While the overall effect of the AMTA payments is insignificant, they exhibit a statistically significant impact on cropping and conservation practices, controlling for the physical characteristics of the land, but exhibit a negative, though statistically insignificant, impact on the the distribution of the physical characteristics that one would expect with changes in land use.

[27] If these payments affect soil erosion through their impact on crop acreage, our results lend support to the argument that the wealth effects of decoupled payments are probably small in magnitude.

[28] While county average disaster payments in the 1991-1993 period were $1.50 per farm acre, the mean disaster payments in the 1996-1998 period were $0.09 per farm acre.

Table 4.3: 2SLS Results - Soil Erosion Estimates (1997)

Variable	Soil Erosion	Corn Insurance	Soybean Insurance	Wheat Insurance
Intercept	0.9378*	0.1571*	0.1503*	0.4850*
	(0.5657)	(0.0712)	(0.0739)	(0.0814)
Corn Returns	−0.0005			
	(0.0022)			
Soybean Returns	0.0019			
	(0.0032)			
Wheat Returns	0.0031)			
	(0.0030)			
Disaster	−0.1472			
	(0.3474)			
Loan Deficiency	−0.1038			
	(0.1055)			
AMTA	0.0193			
	(0.0188)			
Conservation	−0.1900*			
	(0.0429)			
Conservation*EI	0.0193*			
	(0.0034)			
R Factor	0.0103*			
	(0.0018)			
Corn Insurance	7.6226*			
	(3.3202)			
Soybean Insurance	−3.3118			
	(2.9735)			
Wheat Insurance	−5.0710*			
	(1.2260)			
Lagged Pasture	−2.2170*			
	(0.8522)			
Premium		3.2750*	0.1941	0.6272*
		(0.6548)	(0.5575)	(0.3773)
Loss Ratio (LR)		0.0163*	−0.0007	−0.0001
		(0.0058)	(0.0017)	(0.0044)
Premium*LR		−0.2720*	−0.0374	0.0578
		(0.1482)	(0.1673)	(0.1037)
CV Yield		0.0005	0.0093*	−0.0007
		(0.0009)	(0.0011)	(0.0007)
AWC		1.6714*	1.8027*	−0.5561
		(0.3802)	(0.4049)	(0.4680)
Farm Acres		0.0311*	0.0278*	0.0499*
		(0.0052)	(0.0053)	(0.0061)
Fertilizer		−1.1390*	−1.3259*	−1.2035*
		(0.2185)	(0.2202)	(0.2396)
Lagged Income		0.0178*	0.0196*	0.0035
		(0.0059)	(0.0060)	(0.0069)

The standard errors of the coefficients estimates are in parentheses.

The asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

participation from our 2SLS estimation are associated with higher levels of soil erosion, while wheat insurance participation is associated with lower levels of soil erosion. Both coefficient estimates are significant at the 10% level, while soybean insurance participation exhibits no significant impact on soil erosion. Assuming that higher insurance participation is associated with higher planted acreage, our results indicate that counties with a higher production of row crops (corn and soybeans) tend to have higher levels of soil erosion than counties that plant more acreage in small grains (winter wheat).

The insurance participation results from the 1996-1998 period are not generally consistent with those from the 1991-1993 period. This is not surprising since a number of changes in the crop insurance program occurred between these periods. In particular, revenue insurance products were available in the 1996-1998 period, but not in the 1991-1993 period.[29] In addition, efforts to increase producer participation led the government to increase premium rate subsidies by the later period. The biggest difference occurred with respect to the impact of the premium rate on insurance participation. The producer-paid portion of the crop insurance premium rate is positively associated with insurance participation for all three crops, though not significantly associated with soybean insurance participation.

The expected indemnity payment (i.e., loss ratio) is statistically insignificant for soybeans and wheat, while the coefficient of variation of mean yield is statistically significant for only soybean insurance participation. The coefficient estimates on the interaction term indicate that there is not a differential response to premium increases if those increases are conditioned on the expected indemnity payments for soybean or wheat producers. Land quality, as proxied by county average water holding capacity, is associated with significantly higher corn and soybean insurance participation, but lower, though statistically insignificant, wheat insurance participation. This may indicate that producers are more willing to insure more productive land since any systematic crop failure will be associated with higher levels of foregone production. In all three cases, larger farms (in acreage terms) are associated with higher levels of insurance participation, while chemical expenditures are negatively associated with insurance participation. Finally, there is a statistically significant positive relationship between lagged net income and insurance participation with respect

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[29] Attempts were made to model revenue insurance (in addition to yield insurance), but the lack of widespread availability and low levels of participation during this period limited the sample size to an unacceptable level.

to corn and soybeans, with no significant impact on wheat insurance participation.

4.5 Conclusions

The goal of this paper is to extend the preliminary work of Goodwin and Smith (2003) evaluating the impact of government program payments and crop insurance on soil erosion. Using a 2SLS framework, we estimate a system of four equations (soil erosion and three insurance participation equations) for a sample of counties where corn, soybeans, and winter wheat make up over 90% of planted acreage in the county. Therefore, our sample includes counties from many of the areas, such as the primary corn and soybean producing areas of the Midwest, that experience high levels of water-induced soil erosion.

Our results indicate that counties that receive higher conservation payments experience lower levels of soil erosion if those payments are conditioned on soil erodibility; otherwise, those payments are positively associated with soil erosion. This is expected since conservation payments are ideally targeted toward land that is more inherently erodible or land that has experienced greater levels of past soil erosion. We find that an increase in disaster payments is associated with a statistically significant increase in soil erosion for the earlier period, but exhibited no significant impact during the later period. In addition, target price-based deficiency payments (1991-1993), loan deficiency payments (1991-1993 and 1996-1998), and AMTA payments (1996-1998) had no statistically significant impact on soil erosion.

Goodwin and Smith found that crop insurance participation (as proxied by the ratio of insured to total crop acres) exhibited a significant negative impact on soil erosion, though the impact was small in magnitude. While they used total participation for all crops in their sample, we estimate separate equations for each crop (corn, soybeans, and winter wheat) in our sample. When using an alternative measure of total insured acres for the three combined crops, our results confirm those of Goodwin and Smith. The results from our estimation of separate insurance participation equations indicate substantial differences across crops. In both sample periods, higher corn insurance participation is associated with significantly higher soil erosion, while wheat insurance participation is associated with significantly lower soil erosion.

To the extent that soil erosion contributes to a reduction in environmental amenities, such a water quality, our results indicate that concerns over the impact of government income support and risk management programs on indicators of environmental quality may be exaggerated. We find that conservation payments are associated with lower levels of soil erosion, but other government program payments seem to have little impact on soil erosion, at least in the areas represented by our sample. On the other hand, crop insurance participation, particularly for corn and wheat, seems to have a significant impact on soil erosion. It should be noted that our results apply only to counties that have a large percentage of total planted acres devoted to corn, soybean, and winter wheat production. Having said that, our sample incorporates many of the areas of primary concern with respect to the impact of agricultural practices on water-induced soil erosion.

Chapter 5

Summary and Conclusions

The environmental impacts of agricultural production activities continue to play a significant role in policy debates concerning the role of the federal government in the agricultural sector of the economy. It has been argued that government policies that reduce the production risk facing a producer create potential incentives for the producer to undertake activities harmful to the environment. For example, the provision of federally-subsidized crop insurance may encourage producers to bring economically marginal land into production. If that land is also more environmentally fragile than land already in production, this reduction in risk provided by federally-subsidized crop insurance could lead to a reduction in environmental quality. In addition to crop insurance, the federal government has provided a myriad of other programs designed, among other things, to provide income support and reduce income variability in the agricultural sector. Some of these program payments are linked to the current production of a particular crop (e.g., deficiency payments), while other program payments (e.g., AMTA payments) are decoupled from current production. If these programs provide incentives to expand production on the extensive margin, they may also lead to reductions in environmental amenities.

In addition to encouraging production on environmentally fragile land, agricultural subsidy and risk management policies provide incentives for producers to alter crop mix, cropping practices (including input use), and conservation practices. If a crop receives higher deficiency payments or insurance premium subsidies, farmers have an incentive to alter production in favor of that crop. If that crop also requires more extensive cultivation and input use, this shift will lead to a reduction in environmental amenities. Government payments that increase the current return to crop production may discourage the implementation of conservation practices that may increase or maintain long-term crop yields at the expense of short-term yield. Government payments that increase the return to crop production may also decrease the incentive to shift land into less environmentally damaging uses, such as pasture or range.

While much attention has been focused on the impact of government policies on water quality, soil erosion is a key indicator of changes in environmental quality. The extent of soil erosion on agricultural land is dependent on the specific use of the land (e.g., cultivated vs. noncultivated cropland), the level of cover vegetation, the physical and chemical characteristics of the soil, and the agricultural practices (including cropping and conservation) employed on the land. If agricultural subsidy and risk management policies have the potential to alter land use, cropping practices, and conservation practices, they may contribute to increases in soil erosion. In addition to reducing future crop yields, soil erosion increases leaching and surface runoff which contributes to water quality degradation, habitat destruction, and flooding associated with increases in sedimentation.

This study attempted to address some fundamental questions related to the relationship between government agricultural risk management and income support policies and soil erosion. Chapter 2 addressed the validity of the conventional wisdom that economically marginal land is also environmentally fragile. We used mean crop yields as our measure of economic marginality.[1] The soil erodibility index from the National Resources Inventory (NRI) was employed as the measure of environmental marginality. Our study employed both county-level (NASS crop yield) and individual site (SOILS-5 estimated crop yield) data. As a result, we conducted our research at both the site and aggregate (i.e., county) level.

To test the conventional wisdom, we looked at the distribution of crop yields across soil erodibility classes. Conventional wisdom would imply that lower mean crop yields (an indication of economic marginality) should be associated with higher levels of soil erodibility. Therefore, one should expect that mean crop yields would decline over a range of classes indicating increasing soil erodibility. Our results indicate that mean crop yields (SOILS-5 and NASS) generally diminished as the level of erodibility increased, though higher yields were often found in classes exhibiting higher levels of erodibility. These results are somewhat consistent with previous findings (Heimlich (1989)) that mean yield and soil erodibility are weakly associated, though the general trend of diminishing mean yields as levels of soil

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[1] We also used the coefficient of variation of mean crop yield, a measure of yield variability, as an additional proxy for economic marginality.

erodibility increase provide some support to those espousing the conventional wisdom.

In addition, we conducted a more detailed analysis by regressing mean crop yields on the erodibility index and a set of conditioning variables. This analysis yielded consistent results in support of the conventional wisdom that economically marginal land is also likely to be environmentally fragile, at least with respect to increasing levels of soil erodibility. Although the estimated coefficients were negative and significant, the elasticities were generally small, though increases in the erodibility index from the mean value to values at the 80th and 90th percentile of the index distribution resulted in reductions in yields that ranged from .5% to 5.8% in the SOILS-5 data. We concluded that the association between economic marginality (crop productivity) and environmental marginality (soil erodibility) is much stronger than Heimlich's results indicated. This raises concerns that government policies that encourage production on economically marginal land (i.e., land with low mean crop yields) may lead to increases in soil erosion as more erodible soil is brought into production.

Chapter 3 addressed the impact of the provision of federally-subsidized crop insurance on acreage allocation and input use in the major cotton growing regions in the United States. Given our findings in Chapter 2, a finding that the provision of crop insurance encourages farmers to increase production at the extensive margin would provide support for those expressing concern over the environmental consequences of agricultural risk management and income support policies. In addition, insurance-induced changes in crop mix, acreage allocation, and input use may have implications beyond those related to the environment. For instance, insurance-induced increases in production may reduce the price of the commodity. This would partially offset the impact of other government program payments designed to stabilize farm income variability.

Using county-level data, we modeled insurance participation, acreage allocation, and input use for upland cotton and a major competing crop (soybeans or grain sorghum) for two major cotton producing areas — the Southeast and the Southern Plains states. We estimated our system of equations for two periods (1990-1995 and 1996-2000) that represented the pre-FAIR and post-FAIR policy regimes. To evaluate the impact of insurance participation on crop acreage, we conducted simulations whereby we exogenously reduced premium rates from their mean values and then used our structural model to evaluate the impact on crop insurance participation and crop acreage.

Our empirical results suggest that the demand for crop insurance is quite inelastic, though the elasticity increases during the later period. Contrary to expectations, we found a positive relationship between premium rates and insurance participation during the 1996-2000 period. This may be a result of the introduction of revenue insurance products during this period. Increases in overall participation rates occurred as farmers purchased insurance against revenue (as opposed to only yield) shortfalls. Since premium rates for the revenue coverage are higher than those for yield coverage, the positive relationship between insurance participation and premium rates should not be surprising. This may also be a result of increases in subsidy levels that have reduced the producer-paid portion of the total premium rate, even though the producer-paid premium rate and insurance participation both increased over this period.

With respect to the major question that we addressed, the acreage response to insurance participation is also quite inelastic. Grain sorghum acreage is more responsive to insurance participation than the other two crops, but the elasticities range only from .21 (1990-1995) to .33 (1996-2000). The results of our simulations indicate that large premium rate reductions generate significant changes in insurance participation, but those changes do not result in large changes in planted acreage. The largest changes in acreage occur in the 1996-2000 period, where sorghum acreage changes by 1.5-3.3% and cotton acreage changes by 1.1-1.3% in response to a 30% reduction in premium rates. Soybean acreage changes are much more modest than those for cotton and sorghum.

While our results with respect to upland cotton and grain sorghum in these regions indicate that planted acreage may be more responsive to changes in insurance participation than other crops in other regions, our results do not indicate the type of changes found in Griffin (1996) and Keeton et al. (2000). Our major findings are consistent with those in Goodwin et al. (2004) that indicate that substantial changes in insurance participation would have a modest impact on acreage allocation decisions. Having said that, the results, especially those with respect to grain sorghum acreage, suggest that crops other than those that are frequently studied (e.g., wheat, corn, and soybeans) may exhibit different responses to the provision of insurance. As efforts are made to extend coverage to other agricultural commodities, the impact of crop insurance on acreage response should remain a valid empirical question.

Chapter 4 attempted to extend the work of Goodwin and Smith (2003) analyzing the impact of government program payments and crop insurance on soil erosion. Using a 2SLS framework, we estimated a system of four equations (soil erosion and three insurance participation equations) for a sample of counties where corn, soybean, and winter wheat make up over 80% of planted acreage in each county. Therefore, our sample included counties from many of the areas, such as the primary corn and soybean producing areas of the Midwest, that experience high levels of water-induced soil erosion.

Our results indicate that counties that receive higher conservation payments experience lower levels of soil erosion if those payments are conditioned on soil erodibility; otherwise, those payments are positively associated with soil erosion. This is expected since conservation payments are ideally targeted toward land that is more inherently erodible or land that has experienced greater levels of past soil erosion. We find that an increase in disaster payments is associated with higher levels of soil erosion in the 1991-1993 period, though no association in the 1996-1998 period. All other government program payments (target price-based deficiency payments (1991-1993), loan deficieny payments (1991-1993 and 1996-1998), and AMTA payments (1996-1998) had no statistically significant impact on soil erosion. We also found that higher corn insurance participation is associated with significantly higher soil erosion, while wheat insurance participation is associated with significantly lower soil erosion.

Our overall findings indicate that government programs, particularly federally-subsidized crop insurance, are likely to have a statistically significant, though small, impact on acreage allocation and input use decisions. This impact is also likely to vary by crop and geographic region. We also find support for the conventional wisdom that economically marginal land, as defined by low crop yields, is also likely to exhibit higher levels of soil erodibility than more productive land. If the provision of federally-subsidized crop insurance provides incentives to bring economically marginal land into production, as evidenced by our results in Chapter 3, it is likely that this is also providing incentives to bring more erodible land into production. Since the inherent erodibility of the soil is a major determinant of soil erosion, these insurance-induced changes in land allocation are likely to contribute to higher levels of soil erosion. Finally, our results indicate that some government programs (e.g., conservation and crop insurance) are significantly associated with the level of water-induced soil erosion, though other government program payments, such as deficiency and AMTA payments, do not appear to be associated with soil erosion.

In summary, our findings indicate that the concerns expressed over the impact of agricultural income support and risk management policies on changes in indicators of environmental quality, at least in the case of soil erosion, may overstate the potential impact. While government programs, particularly federally-subsidized crop insurance, appear to affect acreage allocation, input use, and soil erosion, the impact is likely to be small in magnitude and vary by program, crop, and geographic location. Although the impacts may be small in magnitude, future research should account for differences across the myriad of program payments available to the producer, particularly with respect to the impact of insurance participation differences across crops.

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Appendix A

Tables

Table A.1: Variable Definitions and Summary Statistics for Site-Specific Data

Variable	Definition	Mean	Std. Dev.
Cotton (cotton_nirryld)	cotton non-irrigated yield (pounds)	557.6100	201.6164
Corn (corn_nirryld)	corn non-irrigated yield (bushels)	101.5986	32.8398
Soybeans (soybean_nirryld)	soybean non-irrigated yield (bushels)	37.0791	8.6245
Sorghum (sorghum_nirryld)	sorghum non-irrigated yield (bushels)	52.2528	21.3799
Erodibility Index (EI)	average of 1987 and 1992 NRI soil erodibility indices	7.7879	10.4136
Soil Water-Holding Capacity (AWC)	average water holding capacity per inch of soil	0.1701	0.0374
C Factor (CFACT)	average of 1987 and 1992 NRI C Factors	0.2496	0.1071
May Rainfall (MAYRN)	average rainfall in ml. (1961-1990)	91.4313	28.0494
June Rainfall (JUNRN)	average rainfall in ml. (1961-1990)	91.5546	25.9204
July Rainfall (JULRN)	average rainfall in ml. (1961-1990)	86.1122	31.1798
August Rainfall (AUGRN)	average rainfall in ml. (1961-1990)	80.2113	28.5049
May Temp. (MAYTEMP)	average temperature 1961-1990 (Celsius degrees)	16.5793	3.2858
June Temp. (JUNTEMP)	average temperature 1961-1990 (Celsius degrees)	21.4217	2.9472
July Temp. (JULTEMP)	average temperature 1961-1990 (Celsius degrees)	23.9495	2.5841
August Temp. (AUGTEMP)	average temperature 1961-1990 (Celsius degrees)	22.8749	2.6965

Table A.2: Variable Definitions and Summary Statistics for Aggregate Data

Variable	Definition	Mean	Std. Dev.
Cotton (cotton_mean)	county mean cotton yield (pounds)	535.2885	195.6828
Corn (corn_mean)	county mean corn yield (bushels)	91.3328	25.7158
Soybeans (soybean_mean)	county mean soybean yield (bushels)	28.3265	6.7262
Sorghum (sorghum_mean)	county mean sorghum yield (bushels)	55.4756	15.6972
Cotton (cotton_cv)	county CV of cotton yield (pounds)	25.6442	10.6225
Corn (corn_cv)	county CV of corn yield (bushels)	22.0148	9.4693
Soybeans (soybean_cv)	county CV of soybean yield (bushels)	19.6661	7.4606
Sorghum (sorghum_cv)	county CV of sorghum yield (bushels)	20.3083	10.3797
Nonirrigated Land (PERNIRR)	nonirrigated portion of cultivated cropland	0.8564	0.2723
Erodibility Index (AGEI)	county average soil erodibility index	8.4780	7.1384
Soil Water-Holding Capacity (AGAWC)	county average water holding capacity per inch of soil	0.1454	0.0306
C Factor (AGCFACT)	county average C Factor	0.2378	0.0893
May Rainfall (MAYRN)	average rainfall in ml. (1961-1990)	96.8731	28.9933
June Rainfall (JUNRN)	average rainfall in ml. (1961-1990)	93.7055	28.5065
July Rainfall (JULRN)	average rainfall in ml. (1961-1990)	92.8586	36.6809
August Rainfall (AUGRN)	average rainfall in ml. (1961-1990)	86.5090	32.6247
May Temp. (MAYTEMP)	average temperature 1961-1990 (Celsius degrees)	17.2492	3.8390
June Temp. (JUNTEMP)	average temperature 1961-1990 (Celsius degrees)	21.7377	3.4182
July Temp. (JULTEMP)	average temperature 1961-1990 (Celsius degrees)	24.1287	2.9621
August Temp. (AUGTEMP)	average temperature 1961-1990 (Celsius degrees)	23.2933	3.1102

Table A.3: OLS Estimates of SOILS-5 Cotton Yields

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−2969.8183	168.3181	−17.64*
EI	−4.5960	0.1107	−41.50*
AWC	767.5961	23.3254	32.91*
CFACT	73.3343	5.8076	12.63*
MAYRN	27.4431	0.6280	43.70*
JUNRN	−2.2715	1.6431	−1.38
JULRN	−30.6302	1.2335	−24.83*
AUGRN	60.5550	1.8551	32.64*
MAYTEMP	523.8830	21.8830	23.94*
JUNTEMP	−592.6994	41.6895	−14.22*
JULTEMP	415.3241	44.1756	9.40*
AUGTEMP	−206.4125	38.0388	−5.43*
SQMAYTEMP	−10.1609	0.4723	−21.52*
SQJUNTEMP	12.0352	0.7892	15.25*
SQJULTEMP	−10.4937	0.8013	−13.10*
SQAUGTEMP	7.9043	0.6958	11.36*
SQMAYRN	0.0042	0.0015	2.74*
SQJUNRN	−0.0058	0.0018	−3.18*
SQJULRN	−0.0236	0.0010	−24.38*
SQAUGRN	−0.0055	0.0013	−4.23*
MAYRNTEMP	−1.3143	0.0328	−40.07*
JUNRNTEMP	0.0954	0.0672	1.42
JULRNTEMP	1.5117	0.0479	31.53*
AUGRNTEMP	−2.2151	0.0680	−32.57*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.4: OLS Estimates of SOILS-5 Corn Yields

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−14.0091	11.9566	−1.17
EI	−0.5412	0.0075	−71.96*
AWC	277.4048	1.7479	158.71*
CFACT	20.5848	0.6507	31.64*
MAYRN	−0.1777	0.0432	−4.11*
JUNRN	−2.3444	0.0740	−31.67*
JULRN	0.7935	0.0638	12.45*
AUGRN	3.6606	0.0643	56.97*
MAYTEMP	78.3865	1.4139	55.44*
JUNTEMP	−88.8716	3.1794	−27.95*
JULTEMP	44.1034	3.7463	11.77*
AUGTEMP	−16.2867	2.7832	−5.85*
SQMAYTEMP	−2.2875	0.0396	−57.74*
SQJUNTEMP	2.6242	0.0746	35.20*
SQJULTEMP	−1.6104	0.0787	−20.45*
SQAUGTEMP	0.5928	0.0593	10.00*
SQMAYRN	0.0009	0.0002	3.73*
SQJUNRN	0.0005	0.0002	2.11*
SQJULRN	−0.0002	0.0001	−1.47
SQAUGRN	−0.0006	0.0001	−4.30*
MAYRNTEMP	−0.0174	0.0025	−7.10*
JUNRNTEMP	0.1032	0.0036	28.40*
JULRNTEMP	−0.0378	0.0028	−13.56*
AUGRNTEMP	−0.1212	0.0029	−41.20*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.5: OLS Estimates of SOILS-5 Sorghum Yields

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−246.8643	9.2412	−26.71*
EI	−0.5824	0.0104	−55.76*
AWC	92.5393	2.3087	40.08*
CFACT	0.0270	0.5551	0.05
MAYRN	−0.3502	0.0451	−7.76*
JUNRN	0.1379	0.0727	1.90*
JULRN	−0.2231	0.1056	−2.11*
AUGRN	5.6854	0.1163	48.88*
MAYTEMP	−4.2249	1.3185	−3.20*
JUNTEMP	−22.4714	2.6571	−8.46*
JULTEMP	28.2760	3.9683	7.13*
AUGTEMP	3.9975	3.2931	1.21
SQMAYTEMP	0.3340	0.0310	10.78*
SQJUNTEMP	0.1175	0.0569	2.06*
SQJULTEMP	−0.3149	0.0748	−4.21*
SQAUGTEMP	0.0162	0.0630	0.26
SQMAYRN	−0.0005	0.0001	−3.27*
SQJUNRN	0.0003	0.0001	2.56*
SQJULRN	−0.0048	0.0002	−26.26*
SQAUGRN	0.0025	0.0002	12.23*
MAYRNTEMP	0.0394	0.0022	18.00*
JUNRNTEMP	−0.0025	0.0033	−0.77
JULRNTEMP	0.0591	0.0041	14.29*
AUGRNTEMP	−0.2478	0.0045	−54.80*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.6: OLS Estimates of SOILS-5 Soybean Yields

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−92.1451	4.4868	−20.54*
EI	−0.2294	0.0027	−84.50*
AWC	85.2804	0.5611	151.99*
CFACT	3.6567	0.2166	16.88*
MAYRN	0.0806	0.0155	5.20*
JUNRN	−0.4460	0.0273	−16.34*
JULRN	−0.1044	0.0223	−4.69*
AUGRN	1.2487	0.0215	58.17*
MAYTEMP	2.9081	0.5026	5.79*
JUNTEMP	9.3564	1.0643	8.79*
JULTEMP	−17.1989	1.2548	−13.81*
AUGTEMP	13.4301	0.9358	14.35*
SQMAYTEMP	−0.0681	0.0146	−4.67*
SQJUNTEMP	−0.0637	0.0247	−2.58*
SQJULTEMP	0.2470	0.0260	9.50*
SQAUGTEMP	−0.2383	0.0198	−12.01*
SQMAYRN	0.0012	0.0001	15.35*
SQJUNRN	−0.0001	0.0001	−1.42
SQJULRN	−0.0001	0.0000	−2.99*
SQAUGRN	−0.0002	0.0000	−4.91*
MAYRNTEMP	−0.0234	0.0009	−27.25*
JUNRNTEMP	0.0206	0.0013	16.35*
JULRNTEMP	0.0056	0.0011	5.32*
AUGRNTEMP	−0.0437	0.0010	−45.18*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.7: OLS Estimates of NASS Cotton Yields (Mean)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	4816.2418	1951.8351	2.47*
AGEI	−0.2917	1.0953	−0.27
AGCFACT	−160.0767	73.7431	−2.17*
PERNIRR	−280.2744	31.6038	−8.87*
AGAWC	410.7842	403.4304	1.02
MAYRN	−18.7258	6.7747	−2.76*
JUNRN	4.1674	12.4238	0.34
JULRN	−14.9681	15.4890	−0.97
AUGRN	37.9711	16.7521	2.27*
SQMAYRN	0.0368	0.0149	2.47*
SQJUNRN	0.0350	0.0186	1.88*
SQJULRN	−0.0095	0.0081	−1.48
SQAUGRN	0.0249	0.0168	1.04
MAYTEMP	538.4492	342.3026	1.57
JUNTEMP	−1886.7849	804.5096	−2.35*
JULTEMP	552.0553	1227.6480	0.45
AUGTEMP	453.0247	927.9176	0.49
SQMAYTEMP	−10.6537	7.6830	−1.39
SQJUNTEMP	34.0365	15.6353	2.18*
SQJULTEMP	−9.0963	21.6172	−0.42
SQAUGTEMP	−6.8037	16.6999	−0.41
MAYRNTEMP	0.5728	0.3228	1.77*
JUNRNTEMP	−0.4222	0.5222	−0.81
JULRNTEMP	0.7828	0.5602	1.40
AUGRNTEMP	−1.5250	0.6307	−2.42*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.8: OLS Estimates of NASS Corn Yields (Mean)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	31.8053	71.5759	0.44
AGEI	−0.1423	0.0517	−2.75*
AGCFACT	14.7014	4.7349	3.10*
PERNIRR	−32.7562	2.0656	−15.86*
AGAWC	153.7956	15.7651	9.76*
MAYRN	1.8827	0.1992	9.45*
JUNRN	−1.1391	0.2685	−4.24*
JULRN	−0.2196	0.3393	−0.65
AUGRN	0.3356	0.3100	1.08
SQMAYRN	−0.0066	0.0010	−6.50*
SQJUNRN	0.0053	0.0010	5.12*
SQJULRN	0.0033	0.0004	7.81*
SQAUGRN	0.0020	0.0007	3.04*
MAYTEMP	−5.5233	7.7653	−0.71
JUNTEMP	−0.2215	18.0865	−0.01
JULTEMP	−21.1120	23.4481	−0.90
AUGTEMP	28.0794	18.2400	1.54
SQMAYTEMP	−0.3257	0.2216	−1.47
SQJUNTEMP	0.8714	0.4222	2.06*
SQJULTEMP	0.3090	0.4937	0.63
SQAUGTEMP	−0.8341	0.3991	−2.09*
MAYRNTEMP	−0.0236	0.0122	−1.94*
JUNRNTEMP	−0.0031	0.0153	−0.20
JULRNTEMP	−0.0225	0.0135	−1.67*
AUGRNTEMP	−0.0123	0.0131	−0.94

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.9: OLS Estimates of NASS Sorghum Yields (Mean)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−1174.1765	335.0947	−3.50*
AGEI	−0.4074	0.1649	−2.47*
AGCFACT	−29.6441	7.7322	−3.83*
PERNIRR	−14.0862	2.7606	−5.10*
AGAWC	40.6809	31.9521	1.27
MAYRN	−0.1977	0.5954	−0.33
JUNRN	−2.0449	0.9500	−2.15*
JULRN	3.3612	1.4762	2.28*
AUGRN	1.9268	1.2890	1.49
SQMAYRN	0.0040	0.0013	3.16*
SQJUNRN	0.0027	0.0012	2.21*
SQJULRN	−0.0036	0.0014	−2.63*
SQAUGRN	0.0016	0.0023	0.69
MAYTEMP	19.2757	23.9546	0.80
JUNTEMP	−61.6379	70.1259	−0.88
JULTEMP	339.8309	86.4700	3.93*
AUGTEMP	−222.9388	61.9475	−3.60*
SQMAYTEMP	−0.7542	0.5816	−1.30
SQJUNTEMP	1.6941	1.4601	1.16
SQJULTEMP	−6.3871	1.6183	−3.95*
SQAUGTEMP	4.3453	1.1561	3.76*
MAYRNTEMP	−0.0285	0.0280	−1.02
JUNRNTEMP	0.0694	0.0394	1.76*
JULRNTEMP	−0.1008	0.0523	−1.93*
AUGRNTEMP	−0.0698	0.0499	−1.40

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.10: OLS Estimates of NASS Soybean Yields (Mean)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−17.6266	40.6845	−0.43
AGEI	−0.0571	0.0171	−3.32*
AGCFACT	1.8319	1.2287	1.49
PERNIRR	−2.1530	0.5231	−4.12*
AGAWC	54.7830	4.1258	13.28*
MAYRN	0.7967	0.0735	10.84*
JUNRN	−0.5336	0.1009	−5.29*
JULRN	0.0201	0.1274	0.16
AUGRN	0.1655	0.0978	1.69*
SQMAYRN	−0.0020	0.0003	−5.84*
SQJUNRN	−0.0012	0.0003	−3.65*
SQJULRN	0.0002	0.0001	1.13
SQAUGRN	0.0000	0.0001	0.64
MAYTEMP	−16.3109	3.1258	−5.22*
JUNTEMP	30.7008	7.1925	4.27*
JULTEMP	−1.2581	8.4366	−0.15
AUGTEMP	−13.9638	5.5194	−2.53*
SQMAYTEMP	0.2922	0.0873	3.35*
SQJUNTEMP	−0.4784	0.1952	−3.00*
SQJULTEMP	−0.0665	0.1674	−0.40
SQAUGTEMP	0.2633	0.1140	2.31*
MAYRNTEMP	−0.0159	0.0032	−4.95*
JUNRNTEMP	0.0335	0.0050	6.70*
JULRNTEMP	−0.0030	0.0053	−0.57
AUGRNTEMP	−0.0034	0.0039	−0.87

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.11: OLS Estimates of NASS Cotton Yields (C.V.)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	29.0374	120.4326	0.24
AGEI	0.0057	0.0676	0.08
PERNIRR	12.0684	1.9500	6.19*
AGAWC	−100.6626	24.8926	−4.04*
AGCFACT	6.9968	4.5501	1.54
MAYTEMP	25.1246	21.1208	1.19
JUNTEMP	−75.5172	49.6401	−1.52
JULTEMP	107.8065	75.7486	1.42
AUGTEMP	−60.2732	57.2546	−1.05
MAYRN	−0.8374	0.4180	−2.00*
JUNRN	1.0650	0.7666	1.39
JULRN	3.8078	0.9557	3.98*
AUGRN	−2.8920	1.0336	−2.80*
SQMAYTEMP	−0.5501	0.4741	−1.16
SQJUNTEMP	1.4651	0.9647	1.52
SQJULTEMP	−1.6719	1.3338	−1.25
SQAUGTEMP	0.8232	1.0304	0.80
SQMAYRN	−0.0001	0.0009	−0.09
SQJUNRN	−0.0010	0.0012	−0.93
SQJULRN	−0.0013	0.0005	−2.64*
SQAUGRN	−0.0011	0.0010	−1.04
MAYRNTEMP	0.0349	0.0199	1.75*
JUNRNTEMP	−0.0297	0.0322	−0.92
JULRNTEMP	−0.1343	0.0346	−3.88*
AUGRNTEMP	0.1078	0.0389	2.77*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.12: OLS Estimates of NASS Corn Yields (C.V.)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	13.0434	39.1570	0.33
AGEI	0.0315	0.0259	1.22
PERNIRR	12.8966	1.0396	12.41*
AGAWC	−29.8542	8.0497	−3.71*
AGCFACT	−0.4109	2.3716	−0.17
MAYTEMP	18.9711	3.8953	4.87*
JUNTEMP	−32.8970	9.1008	−3.61*
JULTEMP	23.2497	12.1235	1.92*
AUGTEMP	−8.5450	9.1827	−0.93
MAYRN	0.2586	0.1006	2.57*
JUNRN	−0.7714	0.1356	−5.69*
JULRN	0.6958	0.1770	3.93*
AUGRN	−0.0879	0.1554	−0.57
SQMAYTEMP	−0.4129	0.1110	−3.72*
SQJUNTEMP	0.6035	0.2123	2.84*
SQJULTEMP	−0.3910	0.2537	−1.54
SQAUGTEMP	0.1682	0.2007	0.84
SQMAYRN	0.0002	0.0005	0.49
SQJUNRN	−0.0002	0.0005	−0.31
SQJULRN	0.0015	0.0002	−7.15*
SQAUGRN	−0.0014	0.0003	−4.33*
MAYRNTEMP	−0.0197	0.0062	−3.21*
JUNRNTEMP	0.0342	0.0077	4.46*
JULRNTEMP	−0.0163	0.0070	−2.33*
AUGRNTEMP	0.0035	0.0065	0.53

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.13: OLS Estimates of NASS Sorghum Yields (C.V.)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−254.6979	247.8331	−1.03
AGEI	−0.0820	0.1216	−0.67
PERNIRR	8.6888	2.0527	4.23*
AGAWC	−44.5640	24.0031	−1.86*
AGCFACT	9.2867	5.7634	1.61
MAYTEMP	−6.7751	17.6635	−0.38
JUNTEMP	−45.0641	51.6455	−0.87
JULTEMP	−48.2862	63.8973	−0.76
AUGTEMP	112.1075	46.4526	2.41*
MAYRN	0.6468	0.4382	1.48
JUNRN	−0.3214	0.7217	−0.45
JULRN	−0.2323	1.1579	−0.20
AUGRN	1.8776	0.9623	1.95*
SQMAYTEMP	0.1462	0.4296	0.34
SQJUNTEMP	0.9356	1.0759	0.87
SQJULTEMP	0.8570	1.1990	0.71
SQAUGTEMP	−1.9959	0.8673	−2.30*
SQMAYRN	−0.0029	0.0009	−3.11*
SQJUNRN	0.0016	0.0009	1.78*
SQJULRN	−0.0007	0.0012	−0.59
SQAUGRN	−0.0003	0.0020	−0.14
MAYRNTEMP	−0.0081	0.0207	−0.39
JUNRNTEMP	−0.0041	0.0297	−0.14
JULRNTEMP	0.0126	0.0397	0.32
AUGRNTEMP	−0.0661	0.0375	−1.76*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.14: OLS Estimates of NASS Soybean Yields (C.V.)

Variable	Estimate	Standard Error	t-Ratio
INTERCEPT	−97.6451	73.69870	−1.33
AGEI	0.0519	0.0311	1.67*
PERNIRR	4.6761	0.9473	4.94*
AGAWC	−35.70050	7.4728	−4.78*
AGCFACT	−0.5704	2.2251	−0.26
MAYTEMP	4.5839	5.6611	0.81
JUNTEMP	−23.4622	13.0233	−1.80*
JULTEMP	0.5096	15.2721	0.03
AUGTEMP	27.9245	9.9948	2.79*
MAYRN	−0.1959	0.1331	−1.47
JUNRN	−0.0769	0.1828	−0.42
JULRN	−0.2066	0.2306	−0.90
AUGRN	0.2787	0.1770	1.57
SQMAYTEMP	−0.0220	0.1582	−0.14
SQJUNTEMP	0.4743	0.2884	1.64*
SQJULTEMP	−0.0115	0.3031	−0.04
SQAUGTEMP	−0.5256	0.2065	−2.55*
SQMAYRN	0.0024	0.0006	3.98*
SQJUNRN	0.0036	0.0006	5.98*
SQJULRN	−0.0022	0.0003	−8.44*
SQAUGRN	−0.0016	0.0003	−6.09*
MAYRNTEMP	−0.0193	0.0058	−3.31*
JUNRNTEMP	−0.0239	0.0091	−2.64*
JULRNTEMP	0.0265	0.0096	2.77*
AUGRNTEMP	−0.0156	0.0071	−2.19*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.15: Variable Definitions and Summary Statistics for Southern Seaboard/Mississippi Portal (1990-1995)

Variable	Definition	Mean	Std. Dev.
Insurance Participation (Cotton)	liability / maximum possible liability	0.2235	0.2232
Insurance Participation (Soybeans)	liability / maximum possible liability	0.1234	0.1399
Premium (Soybeans)	insurance premium rate (soybeans)	0.1251	0.0815
Premium (Cotton)	insurance premium rate (cotton)	0.0813	0.0432
LR (Soybeans)	historical mean loss ratio (soybeans)	2.2574	1.6443
LR (Cotton)	historical mean loss ratio (cotton)	1.7887	1.6546
CV Yield (Soybeans)	CV of historical soybean yields	24.0963	10.0214
CV Yield (Cotton)	CV of historical cotton yields	27.4714	13.0206
Acres Planted (Soybeans)	acres planted of soybeans (ten thousand)	2.4496	3.8248
Acres Planted (Cotton)	acres planted of cotton (ten thousand)	1.8440	2.6503
Total Acres Planted	county acreage of 9 major field crops (ten thousand)	5.2616	7.5715
Input Usage	fertilizer and chemical expenditures (real $thousand) / planted acre	0.2157	0.3367
Land Capability	proportion of land in capability classes 1 and 2	0.2569	0.1437
Livestock Sales	livestock revenues / total farm sales	0.5070	0.3080
County Acres	total acres in the county (hundred thousand)	3.4705	1.5650
Leaching	county average chemical leaching potential	1.7411	0.5517
Soil Erosion	county average historical soil erosion	1.3225	1.3971
Lagged Net Income	county 5 year average net farm income	8933.2200	12174.5000
D90	dummy variable for 1990	0.1684	0.3743
D91	dummy variable for 1991	0.1687	0.3746
D92	dummy variable for 1992	0.1679	0.3738
D93	dummy variable for 1993	0.1650	0.3712
D94	dummy variable for 1994	0.1647	0.3710
D95	dummy variable for 1995	0.1653	0.3715
DSOUTH	dummy variable for the Southern Seaboard region	0.7302	0.4439

Table A.16: Variable Definitions and Summary Statistics for Prairie Gateway (1990-1995)

Variable	Definition	Mean	Std. Dev.
Insurance Participation (Sorghum)	liability / maximum possible liability	0.1269	0.0922
Insurance Participation (Cotton)	liability / maximum possible liability	0.4393	0.3059
Premium (Sorghum)	insurance premium rate (sorghum)	0.0772	0.0433
Premium (Cotton)	insurance premium rate (cotton)	0.0934	0.0380
LR (Sorghum)	historical mean loss ratio (sorghum)	2.7939	2.6060
LR (Cotton)	historical mean loss ratio (cotton)	2.4594	1.9553
CV Yield (Sorghum)	CV of historical sorghum yields	28.8154	13.2825
CV Yield (Cotton)	CV of historical cotton yields	36.5909	13.4319
Acres Planted (Sorghum)	acres planted of sorghum (ten thousand)	2.1196	2.4763
Acres Planted (Cotton)	acres planted of cotton (ten thousand)	4.4757	6.6113
Total Acres Planted	county acreage of 9 major crops (ten thousand)	11.2240	10.8953
Input Usage	fertilizer and chemical expenditures (real $thousand)/planted acre	0.0584	0.0853
Land Capability	proportion of land in capability classes 1 and 2	0.2508	0.1753
Livestock Sales	livestock revenues / total farm sales	0.6585	0.2071
County Acres	total acres in the county (hundred thousand)	6.6075	4.7217
Leaching	county average chemical leaching potential	1.6549	0.4748
Soil Erosion	county average historical soil erosion	1.0673	1.0162
Lagged Net Income	county 5 year average real net farm income	11188.1400	15470.0700
D90	dummy variable for 1990	0.1666	0.3727
D91	dummy variable for 1991	0.1670	0.3731
D92	dummy variable for 1992	0.1666	0.3727
D93	dummy variable for 1993	0.1666	0.3727
D94	dummy variable for 1994	0.1666	0.3727
D95	dummy variable for 1995	0.1666	0.3727

Table A.17: GMM Estimates - Southern Seaboard/Mississippi Portal (1990-1995)

Variable	Estimate	Standard Error	t-Ratio
Soybean Insurance Participation			
Intercept	−0.0345	0.0341	−1.01
Premium	−0.1886	0.1286	−1.47
Premium*LR	0.0260	0.0601	0.43
CV Yield	0.0022	0.0004	6.15*
LR	0.0135	0.0107	1.25
Soybean Acres	0.0069	0.0015	4.75*
County Acres	0.0038	0.0024	1.58
Lagged Net Income	−0.0000	0.0000	−2.32*
Soil Erosion	−0.0063	0.0015	−4.31*
Livestock	0.0295	0.0175	1.69*
Land Capability	−0.0559	0.0225	−2.48*
Fertilizer	1.0286	0.2118	4.86*
D91	−0.0609	0.0079	−7.72*
D92	−0.0528	0.0087	−6.05*
D93	−0.0685	0.0088	−7.82*
D94	−0.0361	0.0089	−4.06*
D95	0.1410	0.0161	8.75*
DSOUTH	−0.0326	0.0111	−2.93*
Cotton Insurance Participation			
Intercept	−0.0193	0.0385	−0.50
Premium	−0.8127	0.2373	−3.43*
Premium*LR	0.2374	0.1123	2.11*
CV Yield	0.0046	0.0008	5.69*
LR	0.0073	0.0092	0.79
Cotton Acres	−0.0008	0.0018	−0.45
County Acres	0.0072	0.0042	1.70*
Lagged Net Income	−0.0000	0.0000	−4.46*
Soil Erosion	−0.0021	0.0021	−1.00
Livestock	0.0530	0.0248	2.14*
Land Capability	0.0093	0.0431	0.22
Fertilizer	0.1173	0.1853	0.63
D91	−0.0037	0.0125	−0.30
D92	0.0166	0.0169	0.98
D93	−0.0032	0.0162	−0.20
D94	−0.0206	0.0137	−1.51
D95	0.2524	0.0167	15.09*
DSOUTH	0.0848	0.0158	5.36*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.17 (continued)

Variable	Estimate	Standard Error	t-Ratio
……………………… Soybean Acreage Response ………………………			
Intercept	−0.0258	0.0821	−0.31
Soybean Acres$_{t-1}$	0.9941	0.0065	152.04*
Insurance Participation	0.2852	0.2888	0.99
County Acres	−0.0325	0.0103	−3.16*
Land Capability	−0.3573	0.0929	−3.85*
Soil Erosion	−0.0060	0.0102	−0.59
D91	−0.1471	0.0557	−2.64*
D92	0.2858	0.0645	4.43*
D93	0.6464	0.0736	8.78*
D94	0.1695	0.0563	3.01*
D95	0.0435	0.0571	0.76
DSOUTH	−0.0991	0.0324	−3.06*
……………………… Cotton Acreage Response ………………………			
Intercept	0.0720	0.0560	1.29
Cotton Acres$_{t-1}$	1.0460	0.0084	125.32*
Insurance Participation	−0.8605	0.1363	−6.31*
County Acres	0.0146	0.0070	2.08*
Land Capability	0.5085	0.0886	5.74*
Soil Erosion	−0.0058	0.0089	−0.65
D91	−0.0141	0.0427	−0.33
D92	−0.3512	0.0372	−9.44*
D93	−0.3284	0.0314	−10.45*
D94	−0.2706	0.0346	−7.82*
D95	0.6108	0.0553	11.06*
DSOUTH	0.1929	0.0305	6.32*
……………………………… Input Usage ………………………………			
Intercept	0.0858	0.0094	9.16*
Participation Soybeans	0.1676	0.0339	4.95*
Participation Cotton	−0.1097	0.0203	−5.41*
Soybean Acres	−0.0039	0.0003	−14.29*
Cotton Acres	0.0021	0.0004	4.74*
Leaching Potential	−0.0005	0.0045	−0.11
Land Capability	0.0183	0.0117	1.56
Organic Matter	−0.0028	0.0023	−1.20
D91	0.0135	0.0045	3.01*
D92	0.0031	0.0046	0.68
D93	0.1176	0.0047	2.53*
D94	−0.0021	0.0039	−0.53
D95	−0.0010	0.0068	−0.15
DSOUTH	0.0372	0.0043	8.70*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.18: GMM Estimates - Prairie Gateway (1990-1995)

Variable	Estimate	Standard Error	t-Ratio
................Grain Sorghum Insurance Participation			
Intercept	0.0653	0.0269	2.43*
Premium	−0.1857	0.1130	−1.64
Premium*LR	0.0290	0.0167	1.73*
CV Yield	0.0023	0.0004	5.84*
LR	0.0026	0.0023	1.10
Sorghum Acres	0.0051	0.0026	5.81*
County Acres	−0.0041	0.0007	−6.17*
Lagged Net Income	0.0000	0.0000	2.27*
Soil Erosion	−0.0238	0.0054	−4.40*
Livestock	−0.0122	0.0122	−1.00
Land Capability	0.0447	0.0324	1.38
Fertilizer	−0.4392	0.2247	−1.95*
D91	0.0046	0.0100	0.46
D92	−0.0304	0.0113	−2.68*
D93	0.0057	0.0108	0.53
D94	−0.0035	0.0103	−0.34
D95	0.1118	0.0128	8.74*
....................Cotton Insurance Participation			
Intercept	0.3469	0.1137	3.05*
Premium	−3.4548	0.7413	−4.66*
Premium*LR	0.9773	0.2785	3.51*
CV Yield	0.0110	0.0014	8.14*
LR	−0.0606	0.0235	−2.57*
Cotton Acres	0.0126	0.0015	8.40*
County Acres	0.0052	0.0027	1.97*
Lagged Net Income	0.0000	0.0000	0.81
Soil Erosion	−0.0505	0.0170	−2.97*
Livestock	−0.0612	0.0528	−1.16
Land Capability	0.2769	0.0957	2.89*
Fertilizer	−5.8673	0.9149	−6.41*
D91	0.0113	0.0239	0.47
D92	0.0861	0.0316	2.73*
D93	0.1019	0.0327	3.11*
D94	0.0551	0.0326	1.69*
D95	0.1941	0.0292	6.65*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.18 (continued)

Variable	Estimate	Standard Error	t-Ratio
Grain Sorghum Acreage Response			
Intercept	−0.7881	0.3311	−2.38*
Sorghum Acres$_{t-1}$	0.6803	0.0500	13.61*
Insurance Participation	3.5328	1.5676	2.25*
County Acres	0.0838	0.0192	4.37*
Land Capability	−0.1471	0.4949	−0.30
Soil Erosion	0.2284	0.1054	2.17*
D91	0.4980	0.1332	3.74*
D92	1.4075	0.2541	5.54*
D93	−0.6779	0.1561	−4.34*
D94	0.1446	0.1313	1.10
D95	−0.0425	0.1762	−0.24
Cotton Acreage Response			
Intercept	0.7139	0.1057	6.75*
Cotton Acres$_{t-1}$	1.0471	0.0105	99.35*
Insurance Participation	0.0141	0.0952	0.15
County Acres	−0.1734	0.1805	−0.96
Land Capability	−0.0044	0.0055	−0.80
Soil Erosion	−0.3563	0.2155	−1.65*
D91	0.0449	0.0389	1.15
D92	−0.2075	0.0837	−2.48*
D93	−1.4196	0.1021	−13.90*
D94	−0.7589	0.0750	−10.12*
D95	−0.9306	0.0859	−10.83*
Input Usage			
Intercept	0.0080	0.0083	0.96
Participation Sorghum	−0.1057	0.0396	−2.67*
Participation Cotton	−0.0124	0.0075	−1.65*
Sorghum Acres	0.0024	0.0007	3.48*
Cotton Acres	0.0005	0.0001	3.51*
Leaching Potential	0.0083	0.0027	3.13*
Land Capability	−0.0227	0.0092	−2.46*
Organic Matter	0.0313	0.0050	6.20*
D91	0.0016	0.0025	0.65
D92	−0.0015	0.0035	−0.42
D93	0.0019	0.0031	0.63
D94	0.0028	0.0031	0.91
D95	0.0247	0.0040	6.16*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.19: Premium Rate Change Simulation Results- Southern Seaboard/Mississippi Portal (1990-1995)

Premium Change	Percent Change in:			
	Soybean Insurance	Cotton Insurance	Soybean Acreage	Cotton Acreage
-30% All Crops	15.2662 ∗ (5.3423)	9.8943 ∗ (2.2110)	0.2084 (0.2880)	-1.0563 ∗ (0.2841)
-30% Cotton	-2.8593 ∗ (1.2808)	9.7458 ∗ (2.2668)	-0.0357 (0.0504)	-1.0466 ∗ (0.2856)
-30% Soybean	17.6571 ∗ (4.9677	0.1141 (0.3267)	0.2440 ∗ (0.3266)	-0.0116 (0.0344)

Standard errors are in parentheses. Asterisk indicates statistical significance at the $\alpha \leq .10$ level.

Table A.20: Premium Rate Change Simulation Results- Prairie Gateway(1990-1995)

Premium Change	Percent Change in:			
	Sorghum Insurance	Cotton Insurance	Sorghum Acreage	Cotton Acreage
-30% All Crops	7.1184 ∗ (2.2634)	8.6109 ∗ (4.4000)	1.3500 ∗ (0.8217)	0.0392 (0.0961)
-30% Cotton	0.1993 (0.2732)	7.6367 ∗ (4.3695)	0.0367 (0.0591)	0.0346 (0.0876)
-30% Sorghum	6.9325 ∗ (2.2030)	1.0511 ∗ (0.6234)	1.3137 ∗ (0.7974)	0.0046 (0.0117)

Standard errors are in parentheses. Asterisk indicates statistical significance at the $\alpha \leq .10$ level.

Table A.21: Variable Definitions and Summary Statistics for Southern Seaboard/Mississippi Portal (1996-2000)

Variable	Definition	Mean	Std. Dev.
Insurance Participation (Soybeans)	liability / maximum possible liability	0.2833	0.2328
Insurance Participation (Cotton)	liability / maximum possible liability	0.4926	0.2248
Premium (Soybeans)	insurance premium rate (soybeans)	0.0455	0.0401
Premium (Cotton)	insurance premium rate (cotton)	0.0377	0.0340
LR (Soybeans)	historical mean loss ratio (soybeans)	2.7152	7.415
LR (Cotton)	historical mean loss ratio (cotton)	5.2465	22.8409
CV Yield (Soybeans)	CV of historical soybean yields	24.8885	10.5549
CV Yield (Cotton)	CV of historical cotton yields	24.2044	10.2268
Acres Planted (Soybeans)	acres planted of soybeans (ten thousand)	2.6376	4.0176
Acres Planted (Cotton)	acres planted of cotton (ten thousand)	2.1275	2.5519
Total Acres Planted	county acreage of 9 major field crops (ten thousand)	5.2616	7.5715
Input Usage	fertilizer and chemical expenditures (real $thousand) / planted acre	0.2574	0.5037
Land Capability	proportion of land in capability classes 1 and 2	0.2563	0.1434
Livestock Sales	livestock revenues / total farm sales	0.5003	0.3159
County Acres	total acres in the county (hundred thousand)	3.5067	1.5810
Leaching	county average chemical leaching potential	1.7277	0.5537
Soil Erosion	county average historical soil erosion	1.0591	1.1411
Lagged Net Income	county 5 year average net farm income	11035.2800	16164.6100
AMTA Payments	county AMTA payments (real dollars per acre)	8.4042	10.1387
Lagged MLA Payments	1 year lagged county MLA payments (real dollars per acre)	2.5302	5.6775
Lagged Disaster Payments	5 year lagged county disaster payments (real dollars per acre)	2.3171	2.4678
D96	dummy variable for 1996	0.1966	0.3975
D97	dummy variable for 1997	0.1956	0.3967
D98	dummy variable for 1998	0.2198	0.4142
D99	dummy variable for 1999	0.1942	0.3957
DSOUTH	dummy variable for the Southern Seaboard region	0.7158	0.4511

Table A.22: Variable Definitions and Summary Statistics for Prairie Gateway (1996-2000)

Variable	Definition	Mean	Std. Dev.
Insurance Participation (Sorghum)	liability / maximum possible liability	0.2506	0.1445
Insurance Participation (Cotton)	liability / maximum possible liability	0.7541	0.3281
Premium (Sorghum)	insurance premium rate (sorghum)	0.0655	0.0385
Premium (Cotton)	insurance premium rate (cotton)	0.0826	0.0393
LR (Sorghum)	historical mean loss ratio (sorghum)	2.4921	2.5542
LR (Cotton)	historical mean loss ratio (cotton)	3.6324	3.9325
CV Yield (Sorghum)	CV of historical sorghum yields	29.4232	13.4761
CV Yield (Cotton)	CV of historical cotton yields	35.4479	13.1358
Acres Planted (Sorghum)	acres planted of sorghum (ten thousand)	2.2601	2.5218
Acres Planted (Cotton)	acres planted of cotton (ten thousand)	4.7028	7.3364
Total Acres Planted	county acreage of 9 major crops (ten thousand)	11.2240	10.8953
Input Usage	fertilizer and chemical expenditures (real $thousand)/planted acre	0.0755	0.1598
Land Capability	proportion of land in capability classes 1 and 2	0.2516	0.1751
Livestock Sales	livestock revenues / total farm sales	0.6334	0.2184
County Acres	total acres in the county (hundred thousand)	6.5724	4.6497
Leaching	county average chemical leaching potential	1.6543	0.4757
Soil Erosion	county average historical soil erosion	0.9244	0.8697
Lagged Net Income	county 5 year average real net farm income	10712.1800	17801.0600
AMTA Payments	county AMTA payments (real dollars per acre)	6.7280	6.0975
Lagged MLA Payments	1 year lagged county MLA payments (real dollars per acre)	1.9083	3.7561
Lagged Disaster Payments	5 year lagged county disaster payments (real dollars per acre)	0.9794	1.1958
D96	dummy variable for 1996	0.2006	0.4006
D97	dummy variable for 1997	0.2001	0.4002
D98	dummy variable for 1998	0.2006	0.4006
D99	dummy variable for 1999	0.1996	0.3998
D00	dummy variable for 2000	0.1991	0.3994

Table A.23: GMM Estimates - Southern Seaboard/Mississippi Portal (1996-2000)

Variable	Estimate	Standard Error	t-Ratio
………………… Soybean Insurance Participation …………………			
Intercept	0.3016	0.0484	6.23*
Premium	1.6613	0.2467	6.73*
Premium*LR	0.0587	0.0765	0.77
CV Yield	0.0030	0.0008	3.94*
LR	−0.0048	0.0027	−1.79*
Soybean Acres	0.0088	0.0016	5.56*
County Acres	0.0046	0.0031	1.46
Lagged Net Income	−0.0000	0.0000	−1.78*
Soil Erosion	0.0005	0.0028	0.17
Livestock	0.0224	0.0258	0.87
Land Capability	−0.1712	0.0422	−4.06*
Fertilizer	−0.2460	0.3875	−0.63
Disaster Payments	0.0073	0.0021	3.54*
D96	−0.1505	0.0137	−11.02*
D97	−0.1861	0.0132	−14.13*
D98	−0.1454	0.0122	−11.96*
D99	−0.0385	0.0114	−3.36*
DSOUTH	−0.0020	0.0136	−0.15
………………… Cotton Insurance Participation …………………			
Intercept	0.2864	0.0344	8.33*
Premium	5.1236	0.3443	14.88*
Premium*LR	−0.1227	0.0773	−1.59
CV Yield	0.0011	0.0007	1.65*
LR	0.0017	0.0007	2.75*
Cotton Acres	0.0026	0.0018	1.43
County Acres	0.0140	0.0038	3.68*
Lagged Net Income	−0.0000	0.0000	−1.70*
Soil Erosion	−0.0107	0.0029	−3.72*
Livestock	−0.0059	0.0253	−0.23
Land Capability	−0.0298	0.0393	−0.76
Fertilizer	1.1243	0.2533	4.44*
Disaster Payments	0.0130	0.0019	6.74*
D96	−0.2332	0.0136	−17.18*
D97	−0.2179	0.0148	−14.77*
D98	−0.1361	0.0131	−10.42*
D99	−0.0238	0.0124	−1.91*
DSOUTH	−0.0652	0.0168	−3.88*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.23 (continued)

Variable	Estimate	Standard Error	t-Ratio
........................Soybean Acreage Response			
Intercept	0.3586	0.1473	2.43*
Soybean Acres$_{t-1}$	0.9921	0.0081	122.53*
Insurance Participation	−0.5865	0.2289	−2.56*
County Acres	0.0149	0.0139	1.07
Land Capability	−0.0243	0.1313	−0.19
Soil Erosion	0.0088	0.0134	0.66
D96	−0.2729	0.1059	−2.58*
D97	0.1300	0.1101	1.18
D98	−0.5595	0.1090	−5.13*
D99	−0.2146	0.0634	−3.38*
MLA Payments$_{t-1}$	−0.0308	0.0060	−5.16*
Disaster Payments	−0.0088	0.0073	−1.21
AMTA Payments	0.0080	0.0033	2.46*
DSOUTH	0.0187	0.0442	0.42
.... Cotton Acreage Response			
Intercept	−0.3756	0.1403	−2.68*
Cotton Acres$_{t-1}$	0.9549	0.0136	70.29*
Insurance Participation	0.4282	0.1989	2.15*
County Acres	−0.0089	0.0102	−0.88
Land Capability	0.1683	0.1357	1.24
Soil Erosion	0.0057	0.0209	0.27
D96	−0.1861	0.0907	−2.05*
D97	0.1390	0.0901	1.54
D98	0.0370	0.0844	0.44
D99	0.4513	0.0647	6.98*
MLA Payments$_{t-1}$	0.0245	0.0051	4.80*
Disaster Payments	−0.0086	0.0089	−0.97
AMTA Payments	−0.0038	0.0031	−1.22
DSOUTH	0.1153	0.0381	3.03*
.... Input Usage			
Intercept	0.0926	0.0097	9.52*
Participation Soybeans	0.0178	0.0230	0.77
Participation Cotton	−0.0260	0.0192	−1.36
Soybean Acres	−0.0028	0.0004	−7.74*
Cotton Acres	0.0024	0.0004	5.85*
Leaching Potential	0.0047	0.0054	0.87
Land Capability	0.0109	0.0134	0.81
Organic Matter	−0.0071	0.0016	−4.51*
D96	0.0068	0.0048	1.42
D97	0.0089	0.0048	1.85*
D98	0.0097	0.0045	2.17*
D99	0.0075	0.0031	2.42*
DSOUTH	0.0260	0.0045	5.77*

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.24: GMM Estimates - Prairie Gateway (1996-2000)

Variable	Estimate	Standard Error	t-Ratio
................Grain Sorghum Insurance Participation			
Intercept	0.1978	0.0564	3.51*
Premium	1.0625	0.2097	5.07*
Premium*LR	−0.0343	0.0084	−4.08*
CV Yield	0.0018	0.0005	3.78*
LR	0.0002	0.0015	0.10
Sorghum Acres	0.0232	0.0051	4.51*
County Acres	−0.0080	0.0032	−2.46*
Lagged Net Income	−0.0000	0.0000	−4.71
Soil Erosion	−0.0165	0.0081	−2.03*
Livestock	0.0257	0.0221	1.16
Land Capability	0.0520	0.0470	1.11
Fertilizer	0.7962	0.3442	2.31*
Disaster Payments	0.0071	0.0036	2.01*
D96	−0.1938	0.0143	−13.56*
D97	−0.1518	0.0149	−10.17*
D98	−0.0636	0.0175	−3.64*
D99	0.0426	0.0167	2.56*
....................Cotton Insurance Participation			
Intercept	1.0921	0.1037	10.53*
Premium	0.7311	0.5937	1.23
Premium*LR	0.2510	0.1478	1.70*
CV Yield	−0.0022	0.0009	−2.46*
LR	−0.0198	0.0103	−1.93*
Cotton Acres	0.0012	0.0012	0.96
County Acres	0.0013	0.0060	0.21
Lagged Net Income	0.0000	0.0000	0.68
Soil Erosion	−0.0374	0.0143	−2.62*
Livestock	−0.0076	0.0338	−0.23
Land Capability	0.2186	0.0739	2.96*
Fertilizer	−5.2701	0.7607	−6.93*
Disaster Payments	0.0007	0.0032	0.23
D96	−0.2334	0.0287	−8.13*
D97	−0.2770	0.0295	−9.40*
D98	−0.1618	0.0327	−4.95*
D99	0.0295	0.0265	1.11

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.24 (continued)

Variable	Estimate	Standard Error	t-Ratio
Grain Sorghum Acreage Response			
Intercept	−1.4086	0.5202	−2.71*
Sorghum Acres$_{t-1}$	0.5338	0.0623	8.57*
Insurance Participation	2.9790	0.9163	3.25*
County Acres	0.1121	0.0499	2.25*
Land Capability	−0.8805	0.6970	−1.26
Soil Erosion	0.2977	0.1075	2.77*
D96	0.9307	0.2682	3.47*
D97	−0.2492	0.2229	−1.12
D98	0.3395	0.2431	1.40
D99	−0.2000	0.1965	−1.02
MLA Payments$_{t-1}$	−0.0859	0.0230	−3.74*
Disaster Payments	−0.0356	0.0669	−0.53
AMTA Payments	0.1080	0.0215	5.03*
Cotton Acreage Response			
Intercept	−0.4647	0.2353	−1.98*
Cotton Acres$_{t-1}$	1.0118	0.0110	91.60*
Insurance Participation	0.4972	0.2034	2.44*
County Acres	0.0032	0.0127	0.25
Land Capability	0.7267	0.5154	1.41
Soil Erosion	−0.1282	0.0528	−2.43*
D96	−0.3593	0.1582	−2.27*
D97	0.1168	0.1706	0.68
D98	0.1861	0.1692	1.10
D99	0.2428	0.1328	1.83*
MLA Payments$_{t-1}$	0.0403	0.0182	2.21*
Disaster Payments	−0.0423	0.0369	−1.15
AMTA Payments	−0.0098	0.0119	−0.82
Input Usage			
Intercept	0.1527	0.0147	10.37*
Participation Sorghum	0.0206	0.0233	0.88
Participation Cotton	−0.1149	0.0158	−7.26*
Sorghum Acres	−0.0008	0.0009	−0.95
Cotton Acres	0.0004	0.0002	2.29*
Leaching Potential	−0.0097	0.0031	−3.13*
Land Capability	−0.0082	0.0107	−0.77
Organic Matter	−0.0003	0.0038	−0.09
D96	−0.0177	0.0052	−3.41
D97	−0.0257	0.0052	−4.90*
D98	−0.0175	0.0053	−3.28*
D99	0.0008	0.0040	0.19

Asterisks indicate statistical significance at the $\alpha = .10$ or smaller level.

Table A.25: Premium Rate Change Simulation Results- Southern Seaboard/Mississippi Portal (1996-2000)

Premium Change	Percent Change in:			
	Soybean Insurance	Cotton Insurance	Soybean Acreage	Cotton Acreage
-30% All Crops	-8.9468 $*$ (0.9420)	-11.2324 $*$ (0.7680)	0.6343 (0.2548)	-1.1284 $*$ (0.5224)
-30% Cotton	-0.0998 (0.2022)	-11.1033 $*$ (0.7605)	0.0074 (0.0160)	-1.1161 $*$ (0.5165)
-30% Soybean	-8.8378 $*$ (0.8690	-0.1155 (0.1435)	0.6269 $*$ (0.2519)	-0.0122 (0.0178)

Standard errors are in parentheses. Asterisk indicates statistical significance at the $\alpha \leq .10$ level.

Table A.26: Premium Rate Change Simulation Results- Prairie Gateway(1996-2000)

Premium Change	Percent Change in:			
	Sorghum Insurance	Cotton Insurance	Sorghum Acreage	Cotton Acreage
-30% All Crops	-3.8790 (4.0258)	-17.0491 $*$ (9.2244)	-1.4935 (2.6567)	-1.3034 (1.1955)
-30% Cotton	4.4579 (5.0323)	-17.9118 (11.7217)	1.7607 (4.8793)	-1.3640 (1.5828)
-30% Sorghum	-8.7341 $*$ (3.1624)	0.7217 (3.4608)	-3.3130 $*$ (1.4770)	0.0598 (0.3375)

Standard errors are in parentheses. Asterisk indicates statistical significance at the $\alpha \leq .10$ level.

Table A.27: Variable Definitions and Summary Statistics for Soil Erosion Model (1992)

Variable	Definition	Mean	Std. Dev.
Soil Erosion	county average USLE soil erosion measure	3.3113	1.9983
Market Return (Corn)	real return per harvested acre (1991-1993)	−34.0841	45.3304
Market Return (Soybeans)	real return per harvested acre (1991-1993)	6.9648	37.2536
Market Return (Winter Wheat)	real return per harvested acre (1991-1993)	−82.5869	44.6682
Disaster Payments	real disaster payments per farm acre (1991-1993)	1.5017	1.9174
Loan Deficiency Payments	real LDPs per farm acre (1991-1993)	0.0163	0.1225
Deficiency Payments	real deficiency payments per farm acre (1991-1993)	11.9403	8.8068
Conservation Payments	real conservation payments per farm acre (1991-1993)	3.2141	3.5183
Insurance Participation (Corn)	percentage of corn acres insured (1991-1993)	0.2589	0.2276
Insurance Participation (Soybeans)	percentage of soybean acres insured (1991-1993)	0.2179	0.2290
Insurance Participation (Wheat)	percentage of wheat acres insured (1991-1993)	0.1826	0.2575
Lagged Pasture	percentage of acres in pasture (1987)	0.1283	0.1183
Premium (Corn)	producer-paid insurance premium rate (corn)(1991-1993)	0.0554	0.0265
Premium (Soybeans)	producer-paid insurance premium rate (soybeans)(1991-1993)	0.0613	0.0481
Premium (Wheat)	producer-paid insurance premium rate (winter wheat) (1991-1993)	0.0603	0.0288
Loss Ratio (Corn)	historical county average loss ratio (corn)(1986-1990)	2.0479	1.6446
Loss Ratio (Soybeans)	historical county average loss ratio (soybeans) (1986-1990)	1.8780	1.4371
Loss Ratio (Wheat)	historical county average loss ratio (winter wheat) (1986-1990)	2.5891	2.5424
CV Yield (Corn)	coefficient of variation of mean corn yield (1986-1990)	23.3512	10.9862
CV Yield (Soybeans)	coefficient of variation of mean soybean yield (1986-1990)	16.0992	6.9375
CV Yield (Wheat)	coefficient of variation of mean winter wheat yield (1986-1990)	26.7314	12.9742
Lagged Income	county average real net farm income (ten thousand dollars) (1986-1990)	0.8886	1.0605
Chemical Expenditures	county average real chemical expenditures per farm acre (1991-1993)	0.0923	0.0804
Farm Acres	total farm acres (hundred thousand)	2.1937	1.4989
Rainfall Factor	rainfall factor (R) of USLE	191.3562	63.4687
Soil Water-Holding Capacity (AWC)	average water holding capacity per inch of soil	0.1577	0.0247

Table A.28: Variable Definitions and Summary Statistics for Soil Erosion Model (1997)

Variable	Definition	Mean	Std. Dev.
Soil Erosion	county average USLE soil erosion measure	2.7999	1.6605
Market Return (Corn)	real return per harvested acre (1996-1998)	−36.6597	54.1318
Market Return (Soybeans)	real return per harvested acre (1996-1998)	26.1001	42.2168
Market Return (Winter Wheat)	real return per harvested acre (1996-1998)	−11.3163	38.3583
Disaster Payments	real disaster payments per farm acre (1996-1998)	0.0948	0.2643
Loan Deficiency Payments	real LDPs per farm acre (1996-1998)	1.2119	1.0012
AMTA Payments	real AMTA payments per farm acre (1996-1998)	11.5573	7.0661
Conservation Payments	real conservation payments per farm acre (1996-1998)	2.7192	3.0724
Insurance Participation (Corn)	percentage of corn acres insured (1996-1998)	0.5372	0.2369
Insurance Participation (Soybeans)	percentage of soybean acres insured (1996-1998)	0.5213	0.2380
Insurance Participation (Wheat)	percentage of wheat acres insured (1996-1998)	0.4159	0.2492
Lagged Pasture	percentage of acres in pasture (1992)	0.1224	0.1151
Premium (Corn)	producer-paid insurance premium rate (corn)(1996-1998)	0.0337	0.0183
Premium (Soybeans)	producer-paid insurance premium rate (soybeans)(1996-1998)	0.0300	0.0193
Premium (Wheat)	producer-paid insurance premium rate (winter wheat) (1996-1998)	0.0365	0.0332
Loss Ratio (Corn)	historical county average loss ratio (corn)(1991-1995)	1.9994	2.6670
Loss Ratio (Soybeans)	historical county average loss ratio (soybeans) (1991-1995)	1.9357	5.4086
Loss Ratio (Wheat)	historical county average loss ratio (winter wheat) (1991-1995)	2.7430	2.2620
CV Yield (Corn)	coefficient of variation of mean corn yield (1991-1995)	22.2892	10.4843
CV Yield (Soybeans)	coefficient of variation of mean soybean yield (1991-1995)	15.2453	8.1567
CV Yield (Wheat)	coefficient of variation of mean winter wheat yield (1991-1995)	26.8387	13.7375
Lagged Income	county average real net farm income (ten thousand dollars) (1991-1995)	0.9936	1.3092
Farm Acres	total farm acres (hundred thousand)	2.3340	1.5639
Rainfall Factor	rainfall factor (R) of USLE	185.5089	56.5657
Soil Water-Holding Capacity (AWC)	average water holding capacity per inch of soil	0.1581	0.0243