IOWA STATE UNIVERSITY
Digital Repository

Graduate Theses and Dissertations

Iowa State University Capstones, Theses and Dissertations

2008

Essays on land cash rents, biofuels, and their interactions

Xiaodong Du
Iowa State University

Follow this and additional works at: https://lib.dr.iastate.edu/etd

Part of the Economics Commons

Recommended Citation
Du, Xiaodong, "Essays on land cash rents, biofuels, and their interactions" (2008). *Graduate Theses and Dissertations*. 10950.
https://lib.dr.iastate.edu/etd/10950

This Dissertation is brought to you for free and open access by the Iowa State University Capstones, Theses and Dissertations at Iowa State University Digital Repository. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.

المنارة للاستشارات

www.manaraa.com

Essays on land cash rents, biofuels markets, and their interactions

by

Xiaodong Du

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

Program of Study Committee:
Dermot J. Hayes, Co-major Professor
David A. Hennessy, Co-major Professor
John C. Beghin
William M. Edwards
GianCarlo Moschini
Cindy Long Yu

Iowa State University

Ames, Iowa

2008

Copyright © Xiaodong Du, 2008. All rights reserved.

المنارة للاستشارات

www.manaraa.com

DEDICATION

I would like to dedicate this thesis to my wife Fengxia, my daughter Kaitlyn and my son Kevin without whose support I would not have been able to complete this work. I would also like to thank my parents, parents-in-law and the rest of my family and friends for their love and support during the writing of this work.

المنارة للاستشارات
www.manaraa.com

TABLE OF CONTENTS

LIST OF TABLES vi

LIST OF FIGURES vii

ACKNOWLEDGEMENTS viii

ABSTRACT ix

1. GENERAL INTRODUCTION 1

Introduction 1

Conclusions Drawn 3

2. DETERMINANTS OF IOWA CROPLAND CASH RENTAL RATES: TESTING RICARDIAN RENT THEORY 5

Abstract 5

Introduction 6

Methods 10

Data 11

Output and Input Prices 12

Soil Quality 13

Distance to Terminal Market 14

Scale of Livestock Industry 14

Ethanol Plant Effect 15

Urbanization Effect 16

Adoption of Genetically Engineered Crops 17

Expected Government Subsidies 18

المنارة للاستشارات

www.manaraa.com

Estimation 19
Price Data Selection 22
Analysis of Estimation Results 23
Long-run Effect Analysis 25
Conclusion 30
Appendix 31
References 32
3. THE PLANTING REAL OPTION IN CASH RENT VALUATION . . . 41
Abstract 41
Introduction 42
Conceptual Model 44
NPV vs. Real Option Methods 45
Real Option Valuation 46
Comparative Statics of the Switching Option 47
Empirical Model 48
Copula Method 50
Data and Estimation Results 52
The Monte Carlo Simulation 55
Conclusion 58
Appendix 59
Real Option Valuation 59
References 66
4. THE IMPACT OF ETHANOL PRODUCTION ON U.S. AND REGIONAL GASOLINE PRICES AND ON WELFARE 74
Abstract 74
Introduction 75
Previous Work 77
Empirical Analysis 80

المنارة للاستشارات
www.manaraa.com

Background 80
Data 82
Estimation 88
Analysis of Estimation Results 91
Regional Analysis 92
Welfare Analysis 93
The Analytical Model 94
Welfare Estimates 97
Sensitivity Analysis 98
Conclusion 99
Appendix 101
References 103

المنارة للاستشارات
www.manaraa.com

LIST OF TABLES

Table 2.1 Estimates of the Random Effects Model 36

Table 2.2 Estimates of the Error Correction Model 37

Table 2.3 Estimates of Long-run Effect (MG) and Adjustment Speed (PMG) . . 37

Table 3.1 OLS Regression Results for Corn and Soybean Yields 69

Table 3.2 Estimates of Marginal Distributions and the Gaussian Copula 70

Table 3.3 Simulation Results for Real Option Value, 1995-2008 71

Table 3.4 Simulation Results for Changing Correlations, 2008 72

Table 4.1 Summary Statistics 108

Table 4.2 Nelson Complexity Index of Downstream Processing Units 109

Table 4.3 Panel Unit Root Tests Results 109

Table 4.4 Fixed Effects Model Extimates on Crack Ratio and Crack Spread . . . 110

Table 4.5 Panel SUR Estimates on Crack Ratio and Crack Spread 111

Table 4.6 Regression Results on Crack Ratio with Individual PADD Data 112

Table 4.7 Basic Market Parameters 113

Table 4.8 Welfare Changes of Corn, Ethanol, Gasoline/Fuel Markets, 2007 113

المنارة للاستشارات

www.manaraa.com

LIST OF FIGURES

Figure 2.1 Cash Rental Rates, 2007 ($/acre/year) 38

Figure 2.2 County Average Row Crop CSR Index 38

Figure 2.3 Ethanol Plants in Operation, 2007 39

Figure 2.4 Long-run Effects (MG) 39

Figure 2.5 MG/PMG Estimates of Dynamic Adjustments 40

Figure 3.1 Simulated Real Option Value under Corn-Soybean Rotation, 2007 . . . 73

Figure 3.2 Real Option Value under Corn-Corn and Corn-Soybean Rotations, 2007 73

Figure 4.1 Crack Ratio, Jan. 1995 - Mar. 2008 114

Figure 4.2 Deflated 3:2:1 Crack Spread, Jan. 1995 - Mar. 2008 114

Figure 4.3 Annual Equivalent Distillation Capacity (10,000 barrels/steam day) . . 115

Figure 4.4 Annual HHI, 1995-2007 115

Figure 4.5 Corn Market 116

Figure 4.6 Ethanol, Gasoline, and Transportation Fuel Markets 116

المنارة للاستشارات

www.manaraa.com

ACKNOWLEDGEMENTS

I would like to take this opportunity to express my thanks to those who helped me with various aspects of conducting research and the writing of this thesis. First and foremost, Dr. Dermot Hayes and Dr. David Hennessy for their guidance, patience and support throughout this research and the writing of this thesis. Their insights and words of encouragement have often inspired me and renewed my hopes for completing my graduate education. I would also like to thank my committee members for their efforts and contributions to this work: Dr. John Beghin, Dr. William Edwards, Dr. GianCarlo Moschini and Dr. Cindy Yu.

المنارة للاستشارات
www.manaraa.com

ABSTRACT

Farmland cash rental markets is one general theme of this dissertation, with the first two essays addressing specific topics related to cash rental rates. A better understanding of the determinants of local cash rental rates and their adjustments to changing economic conditions is important because an increasing and significant portion of farmland is being farmed by tenant operators. Another common thread connecting all the three essays is that they attempt to analyze the impact of biofuels on cash rents, corn/soybean acreage allocation, and gasoline prices. The first essay seeks to establish the determinants of cropland cash rental rates in Iowa using a unique panel data set. It provides evidence on how responsive rental rates are to national commodity prices, in the short-run and in the long-run. These contributions allow us to comment on how closely the Ricardian Rent Theory approximates real-world rent determination. We find that it is an incomplete explanation, even in the long-run. The second essay is concerned with embedded real option components in cash rental rates. Traditional rent valuation methods are biased downward because they excludes the renter's flexibility to use more up-to-date price information when making crop and input intensity choices. We develop an asset pricing model and employ the Monte Carlo simulation to better understand this planting real option. The third essay explores the negative impact of ethanol production on wholesale gasoline prices. The impact varies considerably across regions and comes at the expense of refiners' profits. Based on a transparent analytical model, the study concludes that a net welfare loss arises from ethanol support policies.

المنارة للاستشارات
www.manaraa.com

1. GENERAL INTRODUCTION

Introduction

Recent biofuel expansion has changed market fundamentals and may give rise to a permanent structural change in agricultural commodity prices. According to the "Land Values and Cash Rents Summary" of the U.S. Department of Agriculture, between spring 2007 and spring 2008, national average cropland cash rents per acre increased by $11, or 13%, while cash rents paid for pastureland rose by $1, or 8.3%. A better understanding of the nature and determinants of farmland cash rents has become increasingly important because a significant portion of farmland is being farmed by tenant farmers. Another fact is that agricultural markets are more closely tied to energy markets because of the increasing demand of biofuel. An analysis of impacts of biofuels on agricultural and energy markets is warranted. This dissertation involves three essays on these issues.

The first essay, "Determinants of Iowa Cropland Cash Rental Rates: Testing Ricardian Rent Theory," addresses the issue of cropland cash rental rates. The objectives of this study are to (1) to find short-run determinants of crop rental prices, including roles of soil quality, relative location, ethanol plant, and crop prices, (2) to analyze the dynamic adjustment process of cash rental rates to changes in output prices, and to compare short- and long-run effects of prices on rent, and (3) to provide evidence on the validity of Ricardian rent theory (RRT). There are relatively few studies on this general topic.

For short-run analysis, following RRT, land rent is the highest bid a tenant farmer can afford to pay for the use of the land. The standard translog variable profit function is employed to model cash rents. Annual survey data of typical cash rental rates per acre of cropland of Iowa over 1987-2007 is applied. We choose soil quality and distance to terminal market for

المنارة للاستشارات
www.manaraa.com

each county as fixed inputs. County-level scale of livestock industry, local ethanol production effect, normalized distance to nearby metropolitan areas, and adoption rate of genetically engineered crops are chosen as county-specific factors influencing local cash rental rates. We explicitly take into account (i) spatial autocorrelation due to neighboring counties, (ii) temporal autocorrelation due to time-lagged behavior of farmland rental agreements, and (iii) individual heterogeneity across counties. Various specification tests suggest that a random effects model is appropriate. For long-run analysis, an error correction model is used to estimate (a) the average long-run effect of expected corn price on cash rental rates, and (b) the potentially heterogeneous, dynamic adjustment path for each county.

The second essay, "The Planting Real Option in Cash Rent Valuation," is concerned with embedded real option components in cash rents. Between entering into a rental agreement and planting, a tenant farmer has the flexibility to "switch" between corn and soybeans and to choose the input application level for the next crop year. The value of this planting flexibility is largely driven by volatile input and output prices. Failure to account for this option value will place downward bias on estimates of what farmers should pay to rent land. In this study, we explicitly derive the real option value and provide empirical estimates on the contribution of the crop switching and input intensity options to cash rent. Using local crop and input prices as well as experimental production data, we quantify the values of these real options by Monte Carlo methods. The multivariate dependence structure among yields and prices are captured by a multivariate Gaussian copula.

The third essay, "The Impact of Ethanol Production On U.S. and Regional Gasoline Prices and On Welfare," quantifies the impact of the increase in ethanol supply on the U.S. gasoline market, employing pooled regional time-series data from January 1995 to March 2008. We separate the impact of ethanol from other forces driving gasoline prices, such as seasonality, crude and product market conditions, refinery capacity, refinery market concentration, unexpected supply disruptions, and gasoline imports. The crack ratio and 3-2-1 crack spread are employed to proxy the profitability of the refining industry. Regional analysis of the ethanol impact is also conducted. Based on the estimated substitution effect of ethanol on gasoline

المنارة للاستشارات
www.manaraa.com

and a transparent analytical model, we investigate the distribution of welfare changes from the ethanol blenders tax credit among producers and consumers in the corn, ethanol, gasoline and transportation fuel markets. The overall welfare impact is estimated.

The three essays are provided in the following chapters.

Conclusions Drawn

The three essays address important issues in farmland rental and energy markets and identify major findings. The results in the first essay indicate that Iowa cash rental rates are largely determined by output/input prices, soil quality, relative location, and other county-specific factors. Cash rents go up by $50 for a $1 increase in corn price in the short run. The marginal value of cropland quality, as represented by row-crop corn suitability rating index, is about $2.11. Ethanol plants are not found to have a significant local effect on cash rental rates, impacting local rental markets mainly through the national futures price. Scale of the local livestock industry, closer proximity to big cities, adoption of genetically engineered crops, and expected government subsidies have significant impacts on local cash rental rates. In addition, changes in crop output prices and government subsidies are found to have long-run effects on cash rental rates. The long-run change in cash rents is approximately $103-$112 for a $1 change in corn price and is reached in about four years. The long-term pass-through of $1 government payment into cash rental rates is about $0.65. The empirical results reject a narrow version of the RRT.

In the second essay, Monte Carlo simulation results show that the average cash rent valuation for the real option approach is 13.5% higher than that for the conventional net present value (NPV) method, in which the input intensity option is 0.47%. Crop planting sequence is shown to impact the real option value. The analysis in the third essay suggests that the growth in ethanol production has caused wholesale gasoline prices to be 14¢ per gallon lower than would otherwise have been the case. Furthermore, the negative impact of ethanol on the retail gasoline prices is found to vary considerably across regions. The Midwest region has the biggest impact at 34¢/gallon, while the Rocky Mountain region had the smallest impact,

المنارة للاستشارات
www.manaraa.com

7¢/gallon. The results indicate that the reduction in the gasoline price comes at the expense of refiners' profits and structural change in the refining industry significantly impact gasoline prices. In addition, welfare estimates suggest a net welfare loss of $0.28 billion from the ethanol support policies.

المنارة للاستشارات
www.manaraa.com

2. DETERMINANTS OF IOWA CROPLAND CASH RENTAL RATES: TESTING RICARDIAN RENT THEORY

Abstract

Based on the Ricardian rent theory, this study employs the variable profit function to analyze the determinants of Iowa cropland cash rental rates using county-level panel data from 1987 to 2007. Accounting for spatial and temporal autocorrelations, responses of local cash rental rates to changes in output prices and other exogenous variables are estimated. We find that Iowa cash rental rates are largely determined by output/input prices, soil quality, relative location, and other county-specific factors. Cash rents go up by $50 for a $1 increase in corn price in the short run. The marginal value of cropland quality, as represented by row-crop corn suitability rating index, is about $2.11. Ethanol plants are not found to have a significant local effect on cash rental rates, impacting local rental markets mainly through the national futures price. Scale of the local livestock industry, closer proximity to big cities, adoption of genetically engineered crops, and expected government subsidies have significant impacts on local cash rental rates. In addition, changes in crop output prices and government subsidies are found to have long-run effects on cash rental rates. The long-run change in cash rents is approximately $103-$112 for a $1 change in corn price and is reached in about four years. The long-term pass-through of $1 government payment into cash rental rates is about $0.65. Our research may be viewed as a test of the Ricardian rent theory where the data reject a narrow version of the theory.

Key words: bargaining, basis, ethanol, rate of adjustment, spatial autocorrelation.

المنارة للاستشارات
www.manaraa.com

Introduction

Iowa is one of the major crop growing states in the United States, producing 18% of U.S. corn and 17% of soybeans in 2007. As a result of rapid expansion in the ethanol industry, the amount of corn used for ethanol production increased from 600 million bushels in 2001 to 2.7 billion bushels in 2007. Biofuel-derived demand for corn pushed up the price of corn, which nearly doubled between September 2006 and December 2007. Farmland is the main financial asset of crop farmers. In 2007, the total value of Iowa's 32.6 million acres of farmland was about $128 billion and the average value per acre was $3,908 (Iowa State University Extension 2007a). A better understanding of the determinants of local cash rental rates is important because, for Iowa, an increasing fraction of farmland is being farmed by tenant operators. Excluding land in government programs, the amount of land that is rented increased from 43% to 59% between 1982 and 2002. By 2002 more than two-thirds of the leased farmland was under a cash rent arrangement (Iowa State University Extension 2004).

In the Ricardian rent theory, rent is defined as "that portion of the produce of the earth, which is paid to the landlord for the use of the original and indestructible powers of the soil" (Ricardo 1821, p. 67). Ricardo argued that rent is what remains from gross farm revenue after all the production costs have been paid. In Ricardo's view, rent is the value of the difference in productivity, which is crucial in determining the existence and magnitude of land rent. Ricardo explained this by pointing out that in the first settling of a country, only the very best lands go under cultivation. When the last piece of land is cultivated, production cost equals the sum of wage cost and the normal rate of profit. If rent on this last piece of land is zero, then farmers are indifferent between farming and not farming. But on the more productive land, higher productivity produces a surplus that is expropriated by the landlord in the form of rent.

Economic theory suggests that higher crop production profits resulting from high grain prices will ultimately accrue to the farmland owners because farmland, not labor, is the most limiting resource in agriculture. It is reasonable to assume that tenant farmers are identical and in plentiful supply since much of farm labor involves reproducible technical skills. Demand for farm labor has fallen in recent times because of mechanization and other labor-saving

المنارة للاستشارات
www.manaraa.com

technologies. From 1960 to 2004, total labor (hired, self-employed and unpaid family) use in Iowa agriculture declined by about 90% (Huffman 2007). Much of this labor has been available to re-enter agriculture, if only because many farmers have reluctantly turned to part-time off-farm employment. Hence, farmland becomes the residual claimant of profits. Farmers bid aggressively to expand their land base, which ensures that rent payments equal the difference between revenues and other costs.

This study presents a hedonic analysis of short- and long-run determinants of Iowa cropland cash rental rates, including the dynamic adjustment process of cash rental rates to changes in output prices and government subsidies. In doing so, it provides evidence on the validity of the Ricardian rent theory. The literature on formal analysis of farmland cash rental rates is limited. Representative is Kurkalova, Burkart, and Secchi (2004) who estimated the cropland cash rental rates in the Upper Mississippi River Basin in 1997 by expressing the per acre cash rental rate as a function of the corn yield estimate. In the literature on seeking to measure the incidence of agricultural subsidies on land rents, several papers have discussed different ways of modeling farmland rental rates. Lence and Mishra (2003) modeled land rents as a function of acreage-weighted corn and soybean revenues and government payments. Goodwin, Mishra, and Ortalo-Magné (2004) developed regressions of cash rents against expected market earnings, expected government payments, and indicators of urban pressure.

The land rent literature is distinct from, but strongly related to, the land price literature. In that literature, land rent is the most widely accepted factor affecting farmland price. Early studies found evidence to support a causal relationship between land rents and farmland prices. They tended to conclude that residual returns, or rents, unidirectionally influence farmland prices (Phipps 1984; Awokuse and Duke 2006). But because of the apparent divergence between comparatively stable farm income levels and continuously increasing land prices, people have sought other theoretical and empirical frameworks to help explain farmland price movements.

The focus of this study is on the farmland rental market instead of the asset market. Compared with land asset prices, land rents more likely reflect optimal pricing behavior as they are less vulnerable to asset bubbles and present less severe transaction costs issues. Although

المنارة للاستشارات
www.manaraa.com

some progress has been made toward finding the relationship between land rents and land prices, the literature has not fully investigated the nature and determinants of land rents. A better grasp of the fundamentals of farmland cash rents might help us better understand land pricing issues. Thus, there is a need to examine what factors influence the level of land rents and how land rents respond to changes in exogenous variables. In this study, a unique data set of local cash rental rates is exploited. It consists of county-level cash rental rates for the state of Iowa from 1987 to 2007. The data were collected from an annual survey conducted by Iowa State University Extension. It appears to be unique because, to our knowledge, no other consistently collected county-level data covers any state in the United States.[1]

Our contributions are three-fold. First, we find the short-run determination of cash rental rates in Iowa. In particular we estimate how they are affected by output/input prices, soil quality, relative location, and other county-specific factors. We also find that cash rents change by \$50 for a \$1 change of corn price in the short run. The marginal value of cropland quality is about \$2.11, as represented by the row-crop corn suitability rating (CSR) index. And ethanol plants are not found to have a statistically significant local effect on cash rental rates, as their effects are largely channeled through national futures prices. Scale of local livestock industry, urban proximity, adoption rate of genetically engineered crops, and expected government subsidies have significant impacts on local cash rental rates. Our second contribution is to contrast short- and long-run responses to corn prices and government subsidies. The long-run response of land rents is approximately \$103-\$112 for a \$1 change in corn price, which could be reached in three to four years. Adjustment paths to the long-run equilibrium vary considerably across the state. The total long-term effect of a \$1 change in direct government subsidy is about \$0.65.

Our third contribution is to provide evidence on the validity of the Ricardian rent theory (RRT) in Ricardo's original and classical application, namely, the farmland rental market. We believe we are the first to do so. Different from farmland in the arid West, where water rights

[1]Most other rental rate datasets have either county-level data for shorter periods of time or long time series data but only across fewer statistical regions. For example, University of Minnesota Extension has collected county-level data from 2002 to 2007. University of Nebraska Extension has data for 1981-2007, but only by agricultural statistical districts.

المنارة للاستشارات
www.manaraa.com

are important, deep-soiled, well-watered farmland in rural Iowa is close to a "commodity" in crop production. Hence, our cash rental rates data are close to ideal for the purpose of testing the theory. In the short-run analysis, the RRT has been straightforwardly applied to farmland rental markets. It seems to handle the observed hedonic characteristics fairly well, giving plausible explanations for the determinants of local cash rental rates. But in the analysis of rent responses to a $1 increase in corn price, it comes up short. By contrast with the average value of $140 predicted by the theory, the rent response in the short run is estimated to be only $50 from the variable profit function. We conjecture that the low estimation result is due to inertia in leasing contract re-negotiations. Inertia can be explained by relationship-specific investments, community ties, and other related issues.

Hence, in addition to contemporaneous and static estimation, we also apply long-term, dynamic analysis. We obtain the long-run price effect of $103-$112, which still doesn't fully cover the theoretical value. We formally test the RRT to conclude that the long-run response of cash rent to a $1 corn price change is less than expected yield to which the price change applied. We speculate that part of the reason for the discrepancy may be that intellectual property rights owned by seed suppliers provide them with bargaining power, so that they benefit in the process of cash rents allocation. In other words, the bargaining assumptions underlying the RRT may not be valid. And some of the disparity may also be explained by price and income supports provided by government programs, which may eliminate cash rent responses to output price movements when prices are low, that is, higher prices are offset by lower subsidies.

The paper proceeds as follows. First, a model of farmland cash rental rates is developed using the variable profit function framework. A more detailed description of data follows. Then we present the estimation method for a random effects model that takes into account spatial and temporal autocorrelations. We also explain and analyze the estimation results. The dynamic effects of corn prices and government subsidies on cash rental rates are examined. Finally, concluding remarks are presented.

المنارة للاستشارات
www.manaraa.com

Methods

Consider a tenant farmer facing a multiple output production technology that has M variable outputs and inputs denoted by $y_i, i \in \{1, 2, ..., M\}$. Here, outputs are positive, $y_i > 0$, and inputs are negative, $y_i < 0$. There are also N fixed inputs denoted by $z_h, h \in \{1, 2, ..., N\}$. At the beginning of a production period, he/she rents land, which is in fixed supply in a certain region. The tenancy involves a formal contractual agreement, and the duration of a contract is for a year, which is renewable and renegotiable annually. In the production period, the tenant farmer makes all the input and production decisions. He/she also pays a fixed cash rental rate to the landowner. Following the RRT, land rent is the highest bid a tenant can afford to pay for the use of the land. It is the rental value which will make the tenant farmer indifferent between farming and not farming.

Let R be the fixed cash rental rate, $p_i, i \in \{1, 2, ..., M\}$ be the output/input prices, and let $x_l, l \in \{1, 2, ..., L\}$ denote region-specific factors. The time variable t is included to proxy technological change, which leads to increased per acre grain yields. For Q, the set of technically feasible output and input choices, the cash rental rate for one unit of land is determined by

$$R(\mathbf{p}; \mathbf{z}, \mathbf{x}, t) = \pi(\mathbf{p}; \mathbf{z}, \mathbf{x}, t) = \max \left\{ \sum_{i=1}^{M} p_i y_i; (\mathbf{y}; \mathbf{z}, \mathbf{x}, t) \in Q \right\}.$$

Here, $\mathbf{y}$, $\mathbf{p}$, $\mathbf{z}$, and $\mathbf{x}$ are the vectors of the outputs/inputs, output/input prices, fixed inputs, and region-specific factors, respectively. Thus, rent is the profit, or residual farm return (farm return less variable costs), obtained from the use of rented land given the production possibilities set Q.

The cash rental rate $R(\mathbf{p}; \mathbf{z}, \mathbf{x}, t)$ has the following properties (Chambers 1988, p. 120), which ensure that a one-to-one relationship exists between the production technology and its dual transformation: (1) homogeneous of degree one in $\mathbf{p}$; and (2) non-decreasing (non-increasing) and convex in p_i if i is an output (input). The convexity of the cash rental rate function in prices $p_i, i \in \{1, 2, ..., M\}$ requires that the Hessian matrix with element $\partial^2\pi/\partial p_i \partial p_j, i, j \in \{1, 2, ..., M\}$ be positive semi-definite.

The transcendental logarithmic function form (Chambers 1988, p. 180; Weaver 1983; McKay,

المنارة للاستشارات
www.manaraa.com

Lawrence, and Vlastuin 1983) is employed for the cash rental rates function and is written as

$$\begin{aligned}\ln(R) &= \alpha_0 + \sum_{i=1}^{M}\alpha_i \ln(p_i) + \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M}\gamma_{ij}\ln(p_i)\ln(p_j) + \sum_{h=1}^{N}\beta_h z_h + \frac{1}{2}\sum_{h=1}^{N}\sum_{k=1}^{N}\phi_{hk}z_h z_k \\ &+ \sum_{i=1}^{M}\sum_{h=1}^{N}\delta_{ih}\ln(p_i)z_h + \sum_{i=1}^{M}\phi_{it}\ln(p_i)t + \sum_{h=1}^{N}\varphi_{ht}z_h t + \sum_{l=1}^{L}\eta_l x_l + \phi_t t + \frac{1}{2}\phi_{tt}t^2 \quad (2.1)\end{aligned}$$

Symmetry conditions need to be imposed to ensure the profit function is fully identifiable. Linear homogeneity of cash rental rates function in prices $p_i, i = 1, 2, ..., M$, requires further restrictions. The restrictions are

$$\text{Symmetry:} \quad \gamma_{ij} = \gamma_{ji}, \quad \phi_{hk} = \phi_{kh}. \quad (2.2)$$

$$\text{Homogeneity:} \quad \sum_{i=1}^{M}\alpha_i = 1, \quad \sum_{i=1}^{M}\gamma_{ij} = 0, \quad \sum_{i=1}^{M}\phi_{it} = 0, \quad \sum_{i=1}^{M}\delta_{ih} = 0. \quad (2.3)$$

We impose the linear homogeneity condition in $\mathbf{p}$ by normalizing all input/output prices and price-related variables by one of the output prices, say, p_M. Thus, equation (2.1) can be rewritten as the following, where $\mathbf{p}^* = (p_1/p_M, p_2/p_M, ..., p_{M-1}/p_M)$ and $R^* = R/p_M$.

$$\begin{aligned}\ln(R^*) &= \alpha_0 + \sum_{i=1}^{M-1}\alpha_i \ln(p_i^*) + \frac{1}{2}\sum_{i=1}^{M-1}\sum_{j=1}^{M-1}\gamma_{ij}\ln(p_i^*)\ln(p_j^*) + \sum_{h=1}^{N}\beta_h z_h + \frac{1}{2}\sum_{h=1}^{N}\sum_{k=1}^{N}\phi_{hk}z_h z_k \\ &+ \sum_{i=1}^{M-1}\sum_{h=1}^{N}\delta_{ih}\ln(p_i^*)z_h + \sum_{i=1}^{M-1}\phi_{it}\ln(p_i^*)t + \sum_{h=1}^{N}\varphi_{ht}z_h t + \sum_{l=1}^{L}\eta_l x_l + \phi_t t + \frac{1}{2}\phi_{tt}t^2 \quad (2.4)\end{aligned}$$

Equation (2.4) is estimated based on the data described in the next section.

Data

In this study, we used annual survey data of typical cash rental rates per acre of cropland for the state of Iowa over the period 1987-2007 as reported in Iowa State University Extension (2007b). Copies of a questionnaire were mailed to potential respondents in March each year. Potential respondents were persons employed in one of the following occupations: (1) agricultural lenders, (2) real estate brokers, (3) professional farm managers, (4) farmers, and (5) landowners. In the survey, the respondents provide information based on their best judgments about typical cash rental rates for cropland at the county level. The survey is to be mailed back by early May. For each county, there are about 15-20 responses by individuals doing business in that county

المنارة للاستشارات
www.manaraa.com

or a neighboring county. This data set provides a reasonably accurate measure of typical cash rents of corn and soybean farmland for Iowa counties.

While initiated in 1980, the actual survey data didn't cover all 99 counties of Iowa until 1997. In order to ensure temporal variation in our panel data set, we choose the cash rental rates data covering 83 counties in Iowa.[2] Of the 99 counties, we include most northern and western counties. The 16 counties in the southeast corner of the state are left out because of data limitations. Most of the missing counties started to collect cash rental rates data after 1995. In addition, proportion of land cash rented in missing counties is below state average (28-31% vs. 37%). The cash rental rates for the 83 counties in 2007 are shown in figure 2.1.

We choose y =(corn, soybean, fertilizer) as the outputs and variable input; z =(soil quality, distance index to terminal market) as fixed inputs. County-level scale of livestock industry, local ethanol production effect, normalized distance to nearby metropolitan areas, adoption rate of genetically engineered crops, and expected government subsidies are chosen as county-specific factors influencing local cash rental rates. Each of these chosen variables and its relationship to local cash rental rates is now discussed in greater detail.

Output and Input Prices

In Iowa, most corn is planted between April 20 and May 10. The optimum time to plant varies from year to year; however, having planting done by mid-May is a goal most producers strive to achieve (Iowa State University Extension 2001). Similarly, the optimum planting time for soybeans is from May 5 to June 1. Crops are harvested from September to November of the same year. In each spring, tenant farmers must make decisions on planting and input choices as well as formulate marketing plans for the new crop year. They can observe and use price information from the futures contracts expiring right after harvest time to formulate harvest price expectations. On the Chicago Board of Trade (CBOT), the December contract for corn and the November contract for soybeans are the first available futures contracts after harvest time. Hence we use spring average prices of corn and soybean futures contracts as expected

[2]Detailed information about missing data, omitted counties, and data treatment are in the Appendix.

المنارة للاستشارات
www.manaraa.com

output prices in our study. They are calculated as the average daily settlement prices for the December (November) maturity futures contract during April for corn (soybeans).[3] The producer price index for nitrogen fertilizer is used as the input price, which can be found in the ERS/USDA data set "U.S. Fertilizer Use and Price."

Soil Quality

Soil quality is the capacity of the soil to function in agricultural production. Corn suitability rating (CSR) index is used in this study, which is developed in Iowa to rate each type of soil for its potential row-crop productivity (Iowa State University Extension 2006). The CSR considers average weather conditions as well as frequency of use of the soil for row-crop production. Ratings range from 100 for soils that have no physical limitations, occur on minimal slopes, and can be continuously row-cropped, to as low as 5 for soils with severe limitations for row crops. Land with a CSR rating below 65 is generally considered to be unsuitable for row crop production.

The CSR can be used to rate the potential yield of one soil against that of another over a relatively long period of time. In our case, we assume the CSR remains unchanged over our sampling period. Each soil type in Iowa has a CSR. By identifying the soil types and acres of each soil type in a tract of land, a weighted average CSR can be computed for the tract. We use the county average row-crop CSR index to measure soil quality in this study, as reported in Iowa State University Extension (2007b). The average row-crop CSR index map of Iowa is shown in figure 2.2.

Since the CSR measures the general soil productivity, good corn farmland is also considered to be good soybean land. Figure 2.2 illustrates that a large proportion of land in Iowa is high-grade farmland and can be planted to crops. Most counties have an average row-crop CSR index above 70. Farmland in North Central Iowa has higher quality than land elsewhere. Southern Iowa has the lowest quality farmland compared with the rest of the state, mainly because it tends to have higher erodibility and more weatherd soils. This includes most of the

[3]The reason we use the average April price is explained in the next section.

المنارة للاستشارات
www.manaraa.com

omitted counties, where survey coverage did not commence until the mid-1990s.

Distance to Terminal Market

Counties located closer to the Mississippi River have a transportation advantage since these locations provide better access to international and domestic terminal markets. For farmers in these counties, it has been beneficial to transport their harvest by waterway, the cheapest mode of transportation. We develop the relative location of each county in both south-north (B_N) and east-west directions (B_W). And these two indices are used to build the following Euclidean metric to reflect a county's relative distance to terminal market and transportation cost $B = \sqrt{B_N^2 + B_W^2}$.

Taking advantage of the rectangle shapes and arrangement of most counties in Iowa, we identify the indices B_N and B_W for the southeast corner of the state (Lee County) as 1 and 2.5, respectively. The indices increase by one as a county locates one county further north or west of the state. The relative location index B is then calculated correspondingly.

Scale of Livestock Industry

Iowa ranked seventh in U.S. cattle production in 2006. Cattle are raised all around the state. Iowa also leads the nation in pork production, raising 25% of U.S. hogs in 2006. The livestock industry has been the Iowa corn grower's most important customer. Prior to the expansion of the ethanol market, two-thirds of Iowa's corn crop had gone to feed livestock. The scale of livestock in a county should increase local corn demand and thus increase cropland rental prices.

We use density of livestock in each county to represent a county's scale of livestock industry. It is obtained by dividing total grain-consuming animal units in each county by its total farmland acres. An animal unit is a standard unit for comparing actual animal numbers for the main types of livestock raised in Iowa, including cattle, hogs, and sheep/lambs. An animal unit is based on the dry-weight quantity of feed consumed by the average milk cow during the base period. We adopted a set of animal unit conversion factors, developed by the U.S.

المنارة للاستشارات
www.manaraa.com

Department of Agriculture (1974), to relate feed consumption for each type of livestock to the feed consumed by the average milk cow.

Data were obtained from various sources. The county-level annual cattle (1987-90, 2001-07), hogs (1987-89), and sheep/lambs (1987-90) quantity data were downloaded from the website of the National Agricultural Statistics Service (NASS 2007). The three years (1992, 1997, and 2002) of Census of Agriculture data from NASS are used to linearly interpolate the missing data. Data of county farmland acres are from 2002 Census of Agriculture.

Ethanol Plant Effect

The effect ethanol plants have on corn price and basis has been an issue investigated in several papers. McNew and Griffith (2005) examined the impact of ethanol plants on local grain market prices by estimating the effects of 12 ethanol plants in the Midwest that opened in 2001 and 2002. They found that these new ethanol plants increased local grain prices. Gallagher, Wisner, and Brubacker (2006) conducted a cross-sectional price-location analysis for 270 cities and towns in Iowa in spring 2003 to determine the impact of ethanol plants on local corn prices. The results showed that for four conventional non-farmer-owned firms, price increases as one gets closer to the processing plants, while five of six farmer cooperatives failed to show any statistically significant effect on nearby prices. Olson, Klein, and Taylor (2007) found the impact of ethanol production on corn basis varies by district in South Dakota from \$0.04 to \$0.27 per bushel, with a state average impact of \$0.24 in 2005.

Iowa had an early start in corn-based ethanol production. By the end of 2007, there were 30 ethanol plants with total production capacity of 2.04 billion gallons. In this study, an index of the ethanol plant effect is constructed by summing a county's corn demand from nearby ethanol plants using $E_{it} = \sum_{n=1}^{N_t} w_{in}(t)C_n$. Here $w_{in}(t)$ is the proportion that county i has in the corn supply area of ethanol plant n at year t. C_n is production capacity of the nth ethanol plant. Each corn supply area is assumed to be a circle centered at the ethanol production facility, and to be proportional to the production capacity of that plant. N_t is the total number of ethanol plants in production at time t. All counties inside each corn supply area share the total supply,

المنارة للاستشارات
www.manaraa.com

i.e., the proportion ranges from 0 to 1 and the sum over all counties is 1. Following opening dates of ethanol plants, we construct the panel data of the effect of ethanol production on all sample counties for the period 1987-2007. Figure 2.3 shows the ethanol plants in operation by the end of 2007 and the corresponding corn supply areas, which are based on the map constructed in Wisner (2006).

But the cash rents data may not be disaggregated enough, spatially and temporally, to fully capture the local effect of ethanol plants. This may be especially true when an ethanol plant is not located at the geographic center of a county. It is difficult to identify the true hinterland of an ethanol plant, as it depends on fine local geography. The vast majority of ethanol production capacity came online since January 2004. This new capacity has been spatially dispersed, but mainly in the North Central and Northwest of the state. We also notice that ethanol demand for corn has affected the corn prices pattern across Iowa since January 2006 (Hart 2007). Typically, by contrast with the strongest basis in East Iowa, North Central and West Iowa tend to have the weakest basis, which is mainly determined by transportation costs. This basis pattern is consistent with what we attempt to capture by the distance to terminal market variable in this study. Many ethanol plants opened between fall 2005 and fall 2007 and this is likely the reason for the basis shift in North Central and Northwest Iowa.

Urbanization Effect

Land price in the farmland market is greatly influenced by development pressure of accessible urban areas (Shi, Phipps, and Colyer 1997). While Iowa is not a rapidly developing state, urban expansion, together with other non-farming motives for purchases, are among the long-term factors influencing Iowa's farmland market (Duffy 2004). Close proximity to big metropolitan areas increases development pressures and could possibly lead to higher cash rental rates.

The influence of urban development on local farmland rental markets should increase with the size of urban population and decrease with the distance between two locations. Hence, the urbanization influence of a metropolitan area on each county is measured by the distance between them, normalized by the population in that area. The urbanization effect index

المنارة للاستشارات
www.manaraa.com

for county i is represented by the minimum value of all urbanization influences as $\mathrm{UE}_i = \min\left(d_{ij}/n_j\right), \forall j$, where d_{ij} is the distance between county i and metropolitan area j, $j \in \{1, 2, ..., 10\}$ in our case, and n_j is the population size of that metropolitan area.

By the ranking for population of metropolitan statistical areas the in U.S. (U.S. Census Bureau 2000), the 10 biggest metropolitan areas in Iowa are chosen. The included areas are Omaha/Council Bluffs, Des Moines, Davenport/Moline/Rock Island, Cedar Rapids, Sioux Falls, Waterloo/Cedar Falls, Sioux City, Iowa City, Dubuque, and Ames. Population data are obtained from the U.S. Census 2000. Google Maps data are used to measure the distances between the geographic center of each county and nearby metropolitan areas.

Adoption of Genetically Engineered Crops

In Iowa there has been widespread adoption of genetically engineered (GE) crops since their introduction in 1996. One of the most important benefits of GE crops has been to confer tolerance to herbicides that are used for weed control (Byrne et al. 2004). Another important benefit of GE crops is to confer protection against insect pests. Pesticide and labor saving effects of GE crops have been long recognized in practice and documented in the literature (Qaim and Zilberman 2003). In addition, the majority of the results of field tests and farm surveys show that GE crops produce slightly higher yields than conventional crops.

Labor savings obtained from less weeding and pesticide spraying lead to a drop in labor demand for a given level of output. With a fixed amount of labor, machinery input, and time available in a planting season, a higher adoption rate of GE crops is expected to result in excess production capacity in the short run. In turn, this should motivate tenant farmers to compete for more farmland through bidding up cash rental rates. From these reasons, we expect that adoption of GE crops should have a significant positive effect on cash rental rates. Herbicide-tolerant soybean adoption rates in the United States, as given by total planting acreage data, are drawn from the ERS/USDA data set "Adoption of Genetically Engineered Crops in the U.S."

المنارة للاستشارات
www.manaraa.com

Expected Government Subsidies

Government subsidy payments have important effects on farmland cash rents. Whether farmers are the ultimate recipients and to what extent they benefit from government payments are still open questions. As tenant farmers sign rental contracts in August of the previous year, government payments are not realized and unobservable. So the cash rental rates depend, in part, on farmers' expectations about the future payments. In terms of estimation, this expectation error biases the estimated coefficients toward zero. In dealing with this difficulty, Roberts, Kirwan, and Hopkins (2003) take advantage of the unusual payments structure in 1997 and use them as an instrumental variable to identify the incidence of government payment on land rents in 1992. They found that \$0.34-\$0.41 of every \$1 of government payment is reflected in the land rents. From Kirwan (2005), we learn that landlords capture \$0.25 of the marginal subsidy. Using Iowa county-level panel data over the 1996-2000 period and one-year lagged subsidy realizations as instruments, Lence and Mishra (2003) concluded that a \$1 additional total government payment pushed up cash rental rates by \$0.13 per acre. Goodwin, Mishra, and Ortalo-Magné (2004) utilize four- or five-year historical averages of county-level total payments to represent expected government payments. They indicate that an additional \$1 in loan deficiency payments raises the cash rents by \$0.57.

Following the lines of Lence and Mishra (2003), we construct one-year lagged county-level government payments on a per acre basis to represent the expected government payments for tenant farmers. Federal-level government commodity payments of 1986-1994 are obtained from the Farm Service Agency of the USDA. They are then divided by the total planted corn and soybeans acres to convert to per acre payments. The resulting payments are multiplied by yields ratio between Iowa and national average to reflect local payment levels. Iowa county-level commodity subsidies for 1995-2006 are downloaded from the website of the Environmental Working Group and divided by sum of acres planted with corn and soybeans to place in dollar per acre units.

المنارة للاستشارات
www.manaraa.com

Estimation

Since cash rental rates are not accounting profits, we do not have a breakdown of profit sources. Therefore it is inappropriate to use the commonly applied seemingly unrelated regressions (SUR) estimation procedure to jointly estimate the parameters in output supply and input demand share equations. Using soybean price as the numéraire price, we consider the estimation of equation (2.4) based on the panel data of 83 counties over 1987 to 2007.

In dealing with this panel data set, we explicitly take into account (1) spatial autocorrelation due to neighboring counties; (2) temporal autocorrelation due to time-lagged behavior of farmland rental agreements; and (3) individual heterogeneity across counties. The county-level data are organized by spatial units of observations. The existence of spatial dependence follows from the existence of a variety of spatial interaction phenomena. The estimations errors of these contiguous counties are correlated. The test result for spatial autocorrelation based on Moran's I statistic (Anselin 1988, p. 101) is $Z_I = 88.74$, and is statistically significant. Farmland rental agreements are also liable to exhibit lagged behavior over time. Temporal autocorrelation in the error term is expected. Applying the Wooldridge test for autocorrelation in panel data (Wooldridge 2002, p. 282), we get the value of the F-statistic as 244.40, which is statistically significant and confirms our expectation.

Next, we account for heterogeneity across counties by using the random effects estimator. To justify the random effects model, a one-sided Breusch and Pagan's Lagrange Multiplier test (Greene 2003, p. 224) for the null hypothesis of no random effects, $\sigma_\mu^2 = 0$, yields a χ_1^2 test statistic of 3281.34, which is statistically significant. However, we are still concerned about possible correlation between the regressors and the random effects. To address this concern, we compute a Hausman test statistic for misspecification (Greene 2003, p. 301), based on the difference between the fixed effects and random effects estimators. This yields a χ_{14}^2 test statistic of 10.45 with $P > \chi_{14}^2 = 0.73$, which is not statistically significant. Therefore, we fail to reject the null hypothesis of exogeneity. Consequently the random effects estimator is found to be both consistent and asymptotically efficient.

With these complications, there is no ready-to-use procedure to estimate equation (2.4).

المنارة للاستشارات
www.manaraa.com

Following the likelihood function derivation in Baltagi et al. (2007), we extend the estimation procedure proposed by Elhorst (2003) to a panel data random effects model accounting for both spatial and temporal autocorrelations.[4] Our panel data regression model is specified as

$$y_{ti} = X'_{ti}\beta + u_{ti} \tag{2.5}$$

where $i \in \{1, ..., N\}$ denotes the cross-section dimension and $t \in \{1, ..., T\}$ denotes the time series dimension. The cash rental rate on the ith county for the tth time period is y_{ti}. The K dimensional vector of explanatory variables defined in equation (2.4) is X_{ti}.

By assumption, disturbance term u_{ti} has random county effects, spatially autocorrelated residual disturbances, and first-order serially correlated residual disturbances. Employing a random effects model, we have the disturbance term for time t:

$$u_t = \mu + \epsilon_t \tag{2.6}$$

where $u_t = (u_{t1}, ..., u_{tN})'$. And $\mu = (\mu_1, \mu_2, ..., \mu_N)'$ denotes the unobserved individual random effects for the counties. We assume $\mu \overset{iid}{\sim} N(0, \sigma^2_\mu)$ to be independent of ϵ. Vector $\epsilon_t = (\epsilon_{t1}, ..., \epsilon_{tN})'$ represents the residual disturbance and can be expressed as

$$\epsilon_t = \delta W \epsilon_t + \nu_t \quad \text{and} \quad \nu_t = \rho \nu_{t-1} + e_t \tag{2.7}$$

where $\nu_t = (\nu_{t1}, ..., \nu_{tN})'$ and $e_t = (e_{t1}, ..., e_{tN})'$. The spatial autocorrelation coefficient satisfying $|\delta| < 1$ is δ, while ρ is the temporal autocorrelation coefficient.

W is the spatial contiguity matrix and is constructed based on the notion of binary contiguity between spatial units, i.e., two counties having a common border of non-zero length are considered to be contiguous. A value of 1 is assigned for the corresponding matrix element; otherwise the element is 0. The diagonal elements of W are all 0 since one spatial unit can't be its own neighbor. And the rows of the W matrix are standardized so that they sum to one.

With the normality assumption of $e_{ti} \sim N(0, \sigma^2_e)$, we have $\nu_{it} \sim N\left(0, \sigma^2_e/(1-\rho^2)\right)$ by equation (2.7). Let $B = I_N - \delta W$, $\theta^2 = \frac{\sigma^2_\mu}{\sigma^2_e}$, $\alpha = \sqrt{\frac{1+\rho}{1-\rho}}$, $d^2 = (\iota^\alpha_T)'\iota^\alpha_T$ with $\iota^\alpha_T = (\alpha, \iota'_{T-1})$, and

[4]The codes are modified from the Matlab code provided by Dr. Elhorst, which is for the random effects model with spatial autocorrelation and available at: http://www.regroningen.nl/irios.html, last visited 08/20/2008.

المنارة للاستشارات
www.manaraa.com

assign ι_T as a vector of ones of dimension T. The log-likelihood function for the panel data regression model can be written as[5]

$$\begin{aligned} l(\beta, \sigma_e^2, \delta, \rho, \theta^2) &= -\frac{NT}{2}\ln(2\pi\sigma_e^2) + \frac{1}{2}N\ln(1-\rho^2) - \frac{1}{2}\sum_{i=1}^{N}\ln\left(1 + d^2(1-\rho)^2\theta^2(1-\delta w_i)^2\right) \\ &\quad + T\sum_{i=1}^{N}\ln(1-\delta w_i) - \frac{1}{2\sigma_e^2}\sum_{t=1}^{T} e_t^{**\prime} e_t^{**} \end{aligned} \tag{2.8}$$

where $e_t^{**} = y_t^{**} - X_t^{**}\beta$, and

$$\begin{aligned} y_t^{**} &= P\overline{y}_\alpha^* + B(y_t^* - \overline{y}_\alpha^*) = (I_N - \delta W)y_t^* + (P\overline{y}_\alpha^* - (I_N - \delta W)\overline{y}_\alpha^*) \\ X_t^{**} &= (I_N - \delta W)X_t^* + \left(P\overline{X}_\alpha^* - (I_N - \delta W)\overline{X}_\alpha^*\right) \end{aligned} \tag{2.9}$$

Here, w_i is the ith characteristic root of W, $\overline{y}_\alpha^*$ is the "α" average of y_t, i.e., $\overline{y}_\alpha^* = y_t^{'} \times \iota_T^\alpha/(\alpha + T-1)$, and $\overline{X}_\alpha^*$ is similarly defined. P is such that $P'P = \left(d^2(1-\rho)^2\theta^2 I_N + (B'B)^{-1}\right)^{-1}$. Here $P = \Lambda^{-\frac{1}{2}}R$, where R is an $N \times N$ matrix in which the ith column is the characteristic vector r_i of $\left(d^2(1-\rho)^2\theta^2 I_N + (B'B)^{-1}\right)^{-1}$. Note that r_i is the same as the characteristic vector of the spatial weight matrix W. And Λ is an $N \times N$ diagonal matrix with the ith diagonal element being $c_i = d^2(1-\rho)^2\theta^2 + 1/(1-\delta w_i)^2$.

Estimates of β and σ_e^2 are then solved as follows:

$$\hat{\beta} = \left(X^{**\prime}X^{**}\right)^{-1}\left(X^{**\prime}y^{**}\right) \quad \text{and} \quad \hat{\sigma_e^2} = \sum_{i=1}^{N} e_t^{**\prime}e_t^{**}/NT \tag{2.10}$$

Substituting $\hat{\beta}$ and $\hat{\sigma_e^2}$ into log-likelihood function (2.8), the concentrated log-likelihood function of δ, ρ and θ^2 is obtained:

$$\begin{aligned} l(\delta, \rho, \theta^2) &= \text{Constant} - \frac{NT}{2}\ln\left(\sum_{t=1}^{T} e_t^{**\prime}e_t^{**}\right) - \frac{1}{2}\sum_{i=1}^{N}\ln\left(1 + d^2(1-\rho)^2\theta^2(1-\delta w_i)^2\right) \\ &\quad + \frac{1}{2}N\ln(1-\rho^2) + T\sum_{i=1}^{N}\ln(1-\delta w_i) \end{aligned} \tag{2.11}$$

In summary, the estimation procedure is as follows: (1) Choose the initial values of δ, ρ and θ^2 in the specified ranges; (2) Given δ, ρ and θ^2, solve for $\hat{\beta}$ from equation (2.10), which is the generalized least square (GLS) estimator of β; (3) Substitute the $\hat{\beta}$ obtained in step 2

[5] See Baltagi et al. (2007) and Elhorst (2003) for details on a very similar derivation.

المنارة للاستشارات
www.manaraa.com

into equation (2.11), then use optimization techniques to obtain maximum likelihood estimates (MLE) of δ, ρ and θ^2; (4) Iterate between step 2 and step 3 until results satisfy a predetermined convergence criterion.

Price Data Selection

Before we get into discussion of the estimation results, one point that needs to be made clear concerns why we use average April futures price as expected output price in our estimation. The actual cash rental rates data collection happens in spring (April) while most rental contracts are entered into in late summer (August) of the previous year. In the annual cash rental rates survey, experts are asked to provide information about "current typical" cash rental rates in their counties. Rental contracts are sometimes renegotiated after major price movements. What happens is that the landowner and tenant farmer sometimes agree to wait until after January to set the rent in the event that prices rise significantly after September 1st. It is not clear whether the experts answer the question with reference to prior August rental agreements or to the market environment pertaining at the time of the survey response.

In order to further determine the information content of cash rental rates data, we follow the idea of a comprehensive specification test (Greene 2003, p. 154). In our case, Model 1 is the model using average year t April price for the year t harvest futures contract price, while Model 0 uses average year $t-1$ August price for the year t harvest contract price. Other model specifications are the same as the variable profit function structure in equation (2.4).

In the unrestricted model, we assume that the actual price in forming the expected output price takes the form of a weighted average of April and August prices, as $\kappa \ln(p_{Apr}) + (1 - \kappa) \ln(p_{Aug})$. Here, p_{Apr} and p_{Aug} are the average April price in year t and August price in year $t-1$, respectively, and κ is a weight between 0 and 1. Model 0 assumes $\kappa = 0$ and Model 1 assumes $\kappa = 1$. We use the concentrated log-likelihood function (2.11) to find the maximum likelihood estimate of κ using grid search. This is a simplified estimation method since κ cannot be estimated separately from other parameters in equation (2.11). The maximum likelihood

المنارة للاستشارات
www.manaraa.com

estimate of κ is 0.95.[6] Applying the likelihood ratio test (Greene 2003, p. 152), we get the value of the χ^2-statistic as 0.56 with $P > \chi_1^2 = 0.55$ and fail to reject $\kappa = 1$. This means that model 1 is the appropriate model for the estimation. Estimates of the parameters in equation (2.4) are given in table 2.1. The parameter estimates for the numéraire output, soybeans, are derived using the symmetry and homogeneity constraints in equations (2.2)-(2.3).

Analysis of Estimation Results

From the estimation results, the coefficients of spatial autocorrelation (δ), temporal autocorrelation (ρ), and the fraction of variance due to unobservable effects (θ^2) are all statistically significant at the 1% level, which confirms our model specification tests. Furthermore, the point estimate of spatial autocorrelation is 0.73 and highly significant. This indicates the existence of important spatial dependencies in the data. The point estimate of the temporal autocorrelation is 0.42 and is also highly significant. This confirms the existence of time-lagged behavior in farmland rental agreements.

All the coefficients of region-specific factors have intuitively correct signs. As expected, livestock density, normalized distance to metropolitan areas, adoption rate of GE crops, and expected government subsidies all significantly affect the local cash rental rates. In addition, livestock density, GE crops' adoption, and expected government subsidies considerably increase what tenant farmers pay to landowners. The urbanization effect is estimated as -0.54 and is highly significant. This indicates that farmland rents are higher for counties closer to big metropolitan areas. The estimated coefficient of ethanol production effect is very small and not significant, which means that production of ethanol plants in Iowa have not been found to have a strong local effect on cash rental rates. We have already included national futures prices as expected output prices, accounting for the global effect of ethanol production. So ethanol production impacts local farmland rental markets mainly through the national futures price.

At the adoption rate level of 2007, the total effect of GE adoption on land rent is about

[6]The detailed grid search results for κ are in the Appendix.

المنارة للاستشارات
www.manaraa.com

$14.19. According to Duffy (2007), compared with non-herbicide tolerant soybeans, total cost savings from labor, fertilizer, and pesticide (but not machinery) of herbicide tolerant soybeans is about $11.30. But seed cost of the GE soybeans is $10 higher per acre, which indicates that by utilizing market power to charge higher seed prices, seed companies benefit in the division of land rent. Evaluated at the sample means, the impact of $1 government payment on cash rents is about $0.08.[7]

Furthermore, evaluated at the sample means of all related variables, the marginal effect of soil quality, represented by CSR, is $2.11, which means that cash rent increases by about $2 with one more CSR point. For relative location, represented by B, the marginal effect is about -$0.39, which indicates that counties locating further west and north tend to have slightly lower cash rent levels. The estimated yields of corn and soybeans implied by the profit function are 50 bushels and 18 bushels per acre, respectively.[8] By the RRT, in which the response of cash rents to a marginal increase in corn price is equal to the estimated yield in quantity, the current period cash rent increase corresponding to a $1 increase in corn price is also about $50. Some reflection on the economic foundations of this response is warranted. Perhaps a change in output price should have both short- and long-term effects on cash rental rates. In other words, past changes in corn prices should affect present cash rental rates, but the incidence of the effects may be distributed across several future time periods. While higher corn prices drive up the local cash rental rates, contract re-negotiation in local markets may exhibit inertia due to community ties, relationship-specific investments (RSIs), and market power issues.

Because the process of contract enforcement is typically difficult and costly, enduring personal relationships and community ties are sometimes important for landlords when selecting tenants. It is also well recognized in the literature that RSIs are positively related with contract duration, especially for fixed cash rent contracts (e.g., Joskow 1987; Bandiera 2005; Jacoby and Mansuri 2006; Yoder et al. 2008). Among the four types of RSIs recognized in Williamson

[7]We will discuss total long-term impact of government subsidies in a later section.

[8]These yields are much lower than typical Iowa yields. We will discuss implications of the disparity at a later juncture.

المنارة للاستشارات
www.manaraa.com

(1983), non-salvageable physical specific assets and human specific assets are most relevant to farmland rental markets. Tenant farmers may make investments in equipment and machinery that are specific to the rented land and may lose values in alternative uses. Some human capital investments, such as learning about capabilities of given land, are tied to specific land and cannot be easily transferred to another landlord-tenant relationship. There are similar RSIs on the landlord side as well. Thus, the landlord and tenant farmer more likely prefer a longer-term contract and may be reluctant to repeatedly negotiate leasing contracts over time. So the adjustment of cash rental rates to long-run equilibrium is expected be a long-term process, which is the topic we turn to in the next section.

Long-run Effect Analysis

In this section, the parameter of interest is the average long-run effect of expected corn price and government subsidies on cash rental rates. An error correction model (ECM) is used to estimate the long-run effect. The ECM is a class of models with a general form equivalent to the traditional autoregressive distributed lag (ARDL) models (Greene 2003, p. 579). We are going to look at two dimensions of the relationship between cash rental rates and expected corn prices or government subsidies: the long-run effect; and the potentially heterogeneous, dynamic adjustment path for each county. To be consistent with what we have done above, we consider the long-run effect by analyzing the relationship between cash rental rates and corn futures prices or government subsidies where all of them are normalized by the corresponding soybean futures prices over the period of 1987-2007.

There are two commonly used estimation procedures in the literature for applying panel data to obtain long-run effects. The first one is the mean group (MG) estimator, which was proposed by Pesaran and Smith (1995). The MG procedure is to obtain a distinct regression estimate for each group or county in our case, and then average the coefficients over all groups to obtain the average effect. Pesaran and Smith (1995) showed that the MG estimation produces consistent estimates of the average of the parameters. The second procedure is referred to as pooled mean group (PMG) estimation, and was introduced in Pesaran, Shin, and Smith (1999).

المنارة للاستشارات
www.manaraa.com

It allows the intercepts, short-run coefficients, and error variances to differ across groups but constrains the long-run multipliers to be the same. It is proved that under some regularity assumptions, both MG and PMG estimates are consistent and asymptotically normal for both stationary and non-stationary regressors.

In the ECM, the error correction rate, the short-run effect, and their standard errors are estimated directly. The long-term multiplier can also be easily calculated. More importantly, the long-run equilibrium relationships between cash rental rates and expected corn price or government subsidy can be justified to be the same across all counties, because of similar climatological conditions, contiguous locations, and technology spillovers affecting them in analogous ways. The individual adjustment path of each county to the long-run equilibrium may differ considerably because of county-specific factors. For example, counties with better-quality farmland and those closer to a big metropolitan area may tend to adjust quicker and more completely to price changes. While imposing the same long-run multipliers, PMG estimation allows for variability among short-run coefficients. This structure in turn allows the dynamic specification, including the individual lag structure, to differ across counties. The MG estimation doesn't impose any parameter constraint, allowing all parameters to vary freely.

Following Pesaran, Shin, and Smith (1999), we formulate the fixed effects panel data model in the error correction representation as

$$\triangle y_{it} = \alpha_i y_{i,t-1} + \beta_i x_{i,t-1} + \sum_{j=1}^{p-1} \gamma_{ij} \triangle y_{i,t-j} + \sum_{j=0}^{q-1} \lambda_{ij} \triangle x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{2.12}$$

where $t \in \{1, 2, ..., T\}$, and $i \in \{1, 2, ..., N\}$; y_{it} and x_{it} are the dependent variable and explanatory variable for county i at time t; $\triangle y_{it} = y_{it} - y_{i,t-1}$, $\triangle x_{it} = x_{it} - x_{i,t-1}$, $\triangle y_{i,t-j}$ and $\triangle x_{i,t-j}$ are j period lagged values of y_{it} and x_{it}; and μ_i represents the fixed effect. The disturbances ε_{it} are assumed to be independently distributed across i and t with mean 0 and variance $\sigma_i^2 > 0$. In our case the dependent variable, y_{it}, is the normalized cash rental rate of county i at time t and x_{it} is the normalized corn futures price or one-year lagged government payment over t. There is no cross-sectional variation in futures prices data.

المنارة للاستشارات
www.manaraa.com

The long-run relationship between y_{it} and x_{it} can be defined by

$$y_{it} = \theta_i x_{it} + \nu_{it}, \quad i \in \{1, 2, ..., N\}$$

where $\theta_i = -\frac{\beta_i}{\alpha_i}$ are the long-run coefficients, and ν_{it} is assumed to be a stationary process.

Equation (2.12) can be rewritten as

$$\triangle y_{it} = \alpha_i \nu_{i,t-1} + \sum_{j=1}^{p-1} \gamma_{ij} \triangle y_{i,t-j} + \sum_{j=0}^{q-1} \lambda_{ij} \triangle x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{2.13}$$

where $\nu_{i,t-1}$ is the error correction term, hence, α_i is the error correction coefficient measuring the adjustment speed toward the long-run equilibrium.

By imposing the long-run homogeneity constraint, $\theta_i = \theta, i \in \{1, 2, ..., N\}$, PMG estimation constrains the long-run coefficients to be the same. The pooled maximum likelihood estimation is applied for parameter estimation. Derivation and computation details are provided in Pesaran, Shin and Smith (1999).[9] Because of the linear nature of (2.12), we can obtain the PMG estimators by

$$\hat{\alpha}_{PMG} = \frac{1}{N}\sum_{i=1}^{N} \tilde{\alpha}_i, \qquad \hat{\beta}_{PMG} = \frac{1}{N}\sum_{i=1}^{N} \tilde{\beta}_i, \qquad \hat{\gamma}_{jPMG} = \frac{1}{N}\sum_{i=1}^{N} \tilde{\gamma}_{ij}, \quad j \in \{1, 2, ..., p-1\},$$

$$\hat{\lambda}_{jPMG} = \frac{1}{N}\sum_{i=1}^{N} \tilde{\lambda}_{ij}, \quad j \in \{0, 1, ..., q-1\}, \qquad \hat{\theta}_{PMG} = \tilde{\theta}.$$

The MG estimation allows for heterogeneity among all the parameters in incorporating county-specific long-run and short-run effects. The estimates of the parameters are as follows:

$$\hat{\alpha}_{MG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\alpha}_i, \qquad \hat{\beta}_{MG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}_i, \qquad \hat{\gamma}_{jMG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\gamma}_{ij}, \quad j \in \{1, 2, ..., p-1\},$$

$$\hat{\lambda}_{jMG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\lambda}_{ij}, \quad j \in \{0, 1, ..., q-1\}, \qquad \hat{\theta}_{MG} = \frac{1}{N}\sum_{i=1}^{N} \left(-\frac{\hat{\beta}_i}{\hat{\alpha}_i}\right).$$

where $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\gamma}_{ij}$, and $\hat{\lambda}_{ij}$ are the OLS estimates for an individual county using (2.12).

The lag order was first chosen for each county on the unrestricted model by using the Akaike information criterion (AIC),[10] subject to a maximum lag of 3. Then, the long-run homogeneity

[9] The codes are modified from the Gauss code provided in the paper. Available at: http://www.econ.cam.ac.uk/faculty/pesaran, last visited 08/20/2008.

[10] Using Bayesian Information Criterion (SBC), we get similar results. In some cases, because of SBC's heavier penalty for lost degrees of freedom, it will lead to a simpler model than AIC (Greene 2003, p. 565).

المنارة للاستشارات
www.manaraa.com

constraint was imposed using these AIC-determined lag orders. Table 2.2 shows the MG and PMG estimation results. The results for individual counties of two sets of regressions are not reported because of limited space. They are all statistically significant. All estimates, MG and PMG, of the long-run multipliers, the error correction coefficient and short-run coefficient are all significant. For the ECM model of cash rents and corn price, the estimates are different to some extent, while for expected government payments, all estimated coefficients are quite similar.

Figure 2.4 reports long-run effects of expected corn prices obtained from the MG estimation procedure over sample counties. It demonstrates that significant long-run price effects are present in most of the counties, and they vary considerably across the state. Also, the distribution of the long-run effects is in line with that of historical cash rental rates. This observation is confirmed by the OLS regression results reported in table 2.3, which suggests that the county cash rental rate for 2007 is highly significant in explaining the variation of long-run price effects. It may be that long-run effects and historical cash rental rates are related in some way to counties' specific factors.

Adjustment speeds, represented by the error correction coefficients, are obtained from the PMG estimation procedure with range from 0.38 to 1. In some counties, the error correction coefficients are 1 since the model selection criterion chooses the static model as the best-fitting model. A full adjustment speed of 1 means that cash rents will adjust to long-run equilibrium instantaneously. The regression results in table 2.3 implicate higher soil quality, which is statistically significant at the 1% level, as a factor in explaining heterogeneity in speeds of adjustment. These results lend some support to the hypothesis that sluggish responses to price movement are due to thinner cropland rental markets, where good land is comparatively scarce.

In general, changes in the corn price have both short-term and long-term effects on cash rental rates. In the long run, the possible size of the changes in cash rental rates will be approximately \$103-\$112, which could be reached in three to four years. The adjustment speed and corresponding dynamic adjustment path to the long-run equilibrium vary across the

المنارة للاستشارات
www.manaraa.com

state and depend mainly on the average soil quality of cropland in a specific county. As shown in figure 2.5, following the price shock at year t, the simultaneous increase is about \$85-94, \$15 increase in year $t+1$, \$2 in year $t+2$, and so on. Similarly, as indicated by the estimation results in table 2.2, the long-term pass-through of \$1 government payment into cash rental rates is about \$0.56-\$0.61 while the short-run effect is about \$0.30-\$0.44.

However, we note that the average yield in Iowa over the 1987-2007 period is 140 bushels per acre. The RRT suggests that the long-run equilibrium level corresponding to \$1 increase of corn price should be around \$140. It is about \$30 more than our long-run effect estimation. To formally test the validity of RRT, we apply the likelihood ratio test on PMG long-run effect estimator. The restricted log likelihood changes from -3265.0984 to -3401.7410 after further restricting the common long-run effect to be \$140. The corresponding likelihood ratio statistic is 273.29. Since the computed value is larger than the critical value of χ^2 distribution with one degree of freedom, 3.842, the hypothesis of the long-run effect being \$140 is rejected at 1% significance level.

Besides estimation error, the price and income supports farmers obtained from U.S. agricultural programs may explain part of this disparity. When the effect of a downward corn price movement is eliminated by government support through a price floor, then cash rents should respond to an increase in corn price only when it is above a certain level. Also, the questionable bargaining power assumption underlying the RRT may provide us with another explanation for incomplete long-run responses. In addition to landlords and tenant farmers, seed suppliers may have some degree of bargaining power in the division of cash rents. Private seed companies are typically well protected by patents, licenses, and other intellectual property rights. These protections, and also seed industry concentration, may have enabled seed companies to capture the benefits of their innovation through prices (Jolly and Lence 2000). In other words, continuing adoption of GE corn and soybeans may have conferred seed companies with significant bargaining power, and seed companies may be able to appropriate some farmland cash rents. So lack of consideration for the role that seed suppliers may play is perhaps another reason why the estimated long-run response in rent to a \$1 increase in corn

المنارة للاستشارات
www.manaraa.com

price is only about 0.80 of what RRT suggests.

Conclusion

In this study, we conduct a short-run and long-run analysis of determination of cropland cash rental rates in Iowa over 1987-2007. The results indicate that the adjustment of cash rental rates to long-run equilibrium is heterogeneous across counties and has a long-term dynamic process, which is possibly linked to local specific factors such as farmland soil quality. The total effects of marginal output price change and government subsidy are analyzed and the validity of Ricardian rent theory is tested.

We have three remarks about future possible extensions to our study. First, the behavior of participants in the division of farmland cash rents can be investigated as a cooperative games. Landlord, tenant farmer, and seed supplier come together to bargain over the surplus, cash rents. Cash rents can be assumed to be divided among them according to the Shapley value (Shapley 1953), which defines the payoff to each individual participant based on his marginal contribution to the surplus. The Shapley value measures bargaining power in this allocation game and pins down the magnitude of rent that each player will receive in the bargaining process. It would allow us to better understand the equilibrium impact of rapidly changing biotechnology on land rents. Our analysis also indicates that this important factor bears further scrutiny.

Another possible extension is to break out a real option component to land rents. After signing a rental agreement in August the previous year, a tenant farmer has the flexibility to switch his planting intention between corn and soybeans. Hence, output futures prices, price volatilities, and price correlations will affect a farmer's planting decision and his willingness to pay for land rents. This real option analysis could help us better understand the determinants of cash rents. Finally, there is the issue of institutional price floors such as the U.S. commodity loan rate program. While the U.S. target price program was terminated in 1996, the loan rate program has been renewed in the 2008 Farm Bill. One can test for asymmetric responses of cash rental rates to corn price when the price is above or below a government price floor.

المنارة للاستشارات
www.manaraa.com

Appendix

A.1. Missing Data Information

County	Missing Years	County	Missing Years
Data included in the study (83 counties)			
Adams	1994	Audubon	1988
Calhoun	1993	Cherokee	1994
Clarke	1989,92,94,95,98	Crawford	1998
Decatur	1993	Dubuque	1995
Fremont	1987,88,89	Ida	1993
Iowa	1995	Jones	1995
Mills	1987	Monona	1993,94,95
O'Brien	1994	Palo Alto	1987,88
Plymouth	1994	Poweshiek	1995
Sac	1993	Taylor	1989,94
Union	1995	Woodbury	1993,94,95
Data not included (16 counties)			
Appanoose	1987-96	Davis	1987-92,94,96
Des Moines	1987-92,94-96	Henry	1987-92,94,96
Jefferson	1987-92,94-96	Keokuk	1987-92,94-96
Lee	1987-92,95-96	Louisa	1987-91,94-96
Lucas	1987-92,94-96	Marion	1987-92,94
Mahaska	1987-92,94-95	Monroe	1987-92,94-96
Van Buren	1987-92,94,96	Wapello	1987-92,94-96
Washington	1987-91,94-96	Wayne	1987-92,96

Note: The missing data for the included counties are linearly interpolated using Matlab. We exclude the counties that have missing data for five or more continuous years. The 16 counties are excluded also because they are spatially contiguous in the southeast corner of Iowa.

المنارة للاستشارات
www.manaraa.com

A.2. Grid Search Result for Price Selection

κ	Log-likelihood	κ	Log-likelihood
0	1230.55	0.5	1313.21
0.8	1351.98	0.9	1355.14
0.94	1355.42	0.95	1355.43
0.96	1355.41	1	1355.15

References

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Awokuse, T.O., and J.M. Duke. 2006. The Causal Structure of Land Price Determinants. *Canadian Journal of Agricultural Economics* 54:237-245.

Baltagi, B.H., B.C. Jung, S.H. Song, and W. Koh. 2007. Testing for Serial Correlation, Spatial Autocorrelation and Random Effects Using Panel Data. *Journal of Econometrics* 140:5-51.

Bandiera, O. 2005. Contract Duration and Investment Incentives: Evidence from Land Tenancy Agreements. *Journal of the European Economic Assiciation* 5:953-986.

Byrne, P., S. Ward, J. Harrington, and L. Fuller. 2004. Transgenic Crops: An Introduction and Resource Guide. Department of Soil and Crop Sciences, Colorado State University. Available at: http://cls.casa.colostate.edu/transgeniccrops/, last visited 08/29/2008.

Chambers, R.G. 1988. *Applied Production Analysis: A Dual Approach*. Cambridge: Cambridge University Press.

Duffy, M. 2004. Iowa Farmland in 2004 - Who Will Farm It? Beginning Farmer Center, Iowa State University Extension.

–. 2007. Estimated Costs of Crop Production in Iowa - 2007. Iowa State University Extension.

Elhorst, J.P. 2003. Specification and Estimation of Spatial Panel Data Models. *International Regional Science Review* 26:244-268.

Gallagher P., R. Wisner, and H. Brubacker. 2006. Price Relationships in Processors' Input Market Areas: Testing Theories for Corn Prices Near Ethanol Plants. *Canadian Journal of Agricultural Economics* 53:117-139.

المنارة للاستشارات
www.manaraa.com

Goodwin, B.K., A.K. Mishra, and F. Ortalo-Magné. 2004. Landowners' Riches: The Distribution of Agricultural Subsidies. Working Paper, School of Business, University of Wisconsin, Madison.

Greene, W.H. 2003. *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

Hart, C. 2007. Shifting Corn Basis Patterns. *Iowa Ag Review* 13(3):8-10.

Huffman, W. 2007. Demand for Farm Labor in the Coastal Fruit and Salad Bowl States Relative to Midland States: Four Decades of Experience. Working Paper, Department of Economics, Iowa State University.

Iowa State University Extension. 2001. Corn Planting Guide. Extension Publication PM1885.

–. 2004. Farmland Ownership and Tenure in Iowa 1982-2002: A Twenty-Year Perspective. Extension Publication PM1983.

–. 2006. Corn Suitability Ratings - An Index to Soil Productivity. Extension Publication PM1168.

–. 2007a. 2007 Iowa Land Value Survey. Extension Publication FM1825.

–. 2007b. Cash Rental Rates for Iowa 2007 Survey. Extension Publication FM1851.

Jacoby, H.G., and G. Mansuri. 2008. Land Tenancy and Non-Contractible Investment in Rural Pakistan. *Review of Economic Study* 75:763-788.

Jolly, R.W., and S. Lence. 2000. Value-added Land Values. *Choices* 15(1):18-23.

Joskow, P.L. 1987. Contract Duration and Relationship-Specific Investments: Empirical Evidence from Coal Markets. *American Economic Review* 77:168-185.

Kirwan, B.E. 2005. The Incidence of U.S. Agricultural Subsidies on Farmland Rental Rates. Working Paper, Department of Agricultural & Resource Economics, University of Maryland.

Kurkalova, L.A., C. Burkart, and S. Secchi. 2004. Cropland Cash Rental Rates in the Upper Mississippi River Basin. Technical Report, Center for Agricultural and Rural Development, Iowa State University.

Lence, S.H., and A.K. Mishra. 2003. The Impacts of Different Farm Programs on Cash Rents. *American Journal of Agricultural Economics* 85:753-761.

McKay, L., D. Lawrence, and C. Vlastuin. 1983. Profit, Output Supply, and Input Demand Functions for Multiproduct Firms: The Case of Australian Agriculture. *International Economic Review* 24:323-339.

المنارة للاستشارات
www.manaraa.com

McNew, K., and D. Griffith. 2005. Measuring the Impact of Ethanol Plants on Local Grain Prices. *Review of Agricultural Economics* 27:164-180.

National Agricultural Statistics Service (NASS). 2007. U.S. and All States County Data - Livestock. Available at: http://www.nass.usda.gov/QuickStats/, last visited 08/29/2008.

Olson, A., N. Klein, and G. Taylor. 2007. The Impact of Increased Ethanol Production on Corn Basis in South Dakota. Paper presented at AAEA annual meeting, Portland OR, 29 July-1 August.

Pesaran, M.H., and R.P. Smith. 1995. Estimating Long-Run Relationships From Dynamic Heterogeneous Panels. *Journal of Econometrics* 68:79-113.

Pesaran, M.H., Y. Shin, and R. Smith. 1999. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association* 94:621-634.

Phipps, T.T. 1984. Land Prices and Farm-Based Returns. *American Journal of Agricultural Economics* 66:422-429.

Qaim, M., and D. Zilberman. 2003. Yield Effects of Genetically Modified Crops in Developing Countries. *Science* 299:900-902.

Ricardo, D. 1821. On the Principles of Political Economy and Taxation (3rd. ed). In P. Sraffa, ed. *The Works and Correspondence of David Ricardo*. vol. 1. Cambridge: Cambridge University Press.

Roberts, J.M., B. Kirwan, and J. Hopkins. 2003. The Incidence of Government Program Payments on Agricultural Land Rents: The Challenges of Identification. *American Journal of Agricultural Economics* 85:762-769.

Shapley, L. 1953. The Value of an N-Person Game. In H.W. Kuhn and R.W. Tucker, ed. *Contributions to the Theory of Games*. Princeton NJ: Princeton University Press, pp. 307- 317.

Shi, Y.J., T.T. Phipps, and D. Colyer. 1997. Agricultural Land Values Under Urbanizing Inuences. *Land Economics* 73:90-100.

U.S. Census Bureau. 2000. Ranking Tables for Population of Metropolitan Statistical Areas: 1990 and 2000 (PHC-T-29). United States Census 2000. Available at: http://www.census.gov/population/cen2000/phc-t29/tab07.pdf, last visited 08/29/2008.

U.S. Department of Agriculture. 1974. Livestock-Feed Relationships National and State. ERS. Statist. Bull. No. 530.

–. 2006. U.S. Fertilizer Use and Price. ERS/USDA Data Sets. Available at: http://www.ers.usda.gov/Data/FertilizerUse/, last visited 08/29/2008.

المنارة للاستشارات
www.manaraa.com

–. 2007. Adoption of Genetically Engineered Crops in the U.S. ERS/USDA Data Sets. Available at: http://www.ers.usda.gov/Data/BiotechCrops/, last visited 08/29/2008.

Weaver, R.D. 1983. Multiple Input, Multiple Output Production Choices and Technology in the U.S. Wheat Region. *American Journal of Agricultural Economics* 65:45-56.

Williamson, O.E. 1983. Credible Commitments: Using Hostages to Support Exchange. *American Economic Review* 73:519-540.

Wisner, R. 2006. Ethanol, Feed Grain Markets, and Longer Term Implications. Paper presented at the Biobased Industry Outlook Conference - Growing the Bioeconomy, Ames IA, 28-29 August.

Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Yoder, J, I. Hossain, F. Epplin, and D. Doye. 2008. Contract Duration and the Division of Labor in Agricultural Land Leases. *Journal of Economic Behavior & Organization* 65:714- 733.

المنارة للاستشارات

www.manaraa.com

Table 2.1 Estimates of the Random Effects Model

	Explanatory Variables	Parameter	Asymp. t-stat.	Z-Value
1	Constant	1.47	0.62	0.54
2	ln(Corn price)	2.20	2.35	0.02
3	ln(Fertilizer price)	-0.71	-1.78	0.08
4	$\frac{1}{2}\ln(\text{Corn price})^2$	1.01	1.25	0.21
5	ln(Corn price) $\times$ ln(Fertilizer price)	-2.46	-8.29	< 0.001
6	$\frac{1}{2}\ln(\text{Fertilizer price})^2$	-3.51	-8.94	< 0.001
7	CSR	0.05	0.95	0.34
8	B	0.10	1.13	0.26
9	$\frac{1}{2}(\text{CSR})^2$	-0.00034	-0.59	0.55
10	$\frac{1}{2}B^2$	0.00087	0.35	0.72
11	CSR $\times B$	-0.0012	-1.35	0.18
12	ln(Corn price) $\times$ CSR	0.000088	0.019	0.98
13	ln(Corn price) $\times B$	-0.0026	-0.21	0.84
14	ln(Fertilizer price) $\times$ CSR	0.002	0.84	0.39
15	ln(Fertilizer price) $\times B$	0.0049	0.76	0.45
16	ln(Corn price) $\times t$	0.099	5.88	< 0.001
17	ln(Fertilizer price) $\times t$	0.15	9.95	< 0.001
18	CSR $\times t$	-0.00044	-3.09	0.002
19	$B \times t$	-0.00067	-1.72	0.09
20	t	0.12	4.85	< 0.001
21	t^2	-0.015	-18.71	< 0.001
22	Scale of livestock industry	0.054	2.38	0.02
23	Ethanol plant effect	0.000038	0.13	0.90
24	Urbanization effect	-0.54	-10.60	< 0.001
25	Adoption of GE crops	0.93	18.83	< 0.001
26	Expected subsidies	0.0040	5.04	< 0.001
27	θ^2	0.66	8.94	< 0.001
28	δ	0.73	35.90	< 0.001
29	ρ	0.42	15.85	0.001
	R^2	0.9870		
	adjusted R^2	0.9868		
	Number of cross-sections	83		
	Number of years	21		
	Total number of observations	1743		

المنارة للاستشارات
www.manaraa.com

Table 2.2 Estimates of the Error Correction Model

	Corn price change		Subsidy	
Parameter	MG	PMG	MG	PMG
Long-run multiplier	111.86 (3.07)	103.29 (2.04)	0.557 (0.020)	0.613 (0.022)
Error correction coefficient	-0.85 (0.025)	-0.82 (0.027)	-0.71 (0.032)	-0.71 (0.033)
Short-run coefficient	93.87 (3.53)	84.70 (2.74)	0.44 (0.020)	0.36 (0.012)

Note: standard error is in the parenthesis.

Table 2.3 Estimates of Long-run Effect (MG) and Adjustment Speed (PMG)

	Long Run Effect			Adjustment Speed		
Explanatory Variables	Parameter	t-stat.	Z-Value	Parameter	t-stat.	Z-Value
Constant	280.97	3.72	< 0.001	0.76	1.22	0.23
Rent 2007	0.42	1.79	0.08	-0.0075	-3.82	< 0.001
CSR	-2.12	-3.48	0.001	0.021	4.24	< 0.001
B	-1.74	-1.23	0.22	0.047	4.00	< 0.001
Urbanization effect	-0.77	-2.20	0.03	-0.012	-4.29	< 0.001
R^2	0.3257			0.3158		
adjusted R^2	0.2911			0.2807		

المنارة للاستشارات
www.manaraa.com

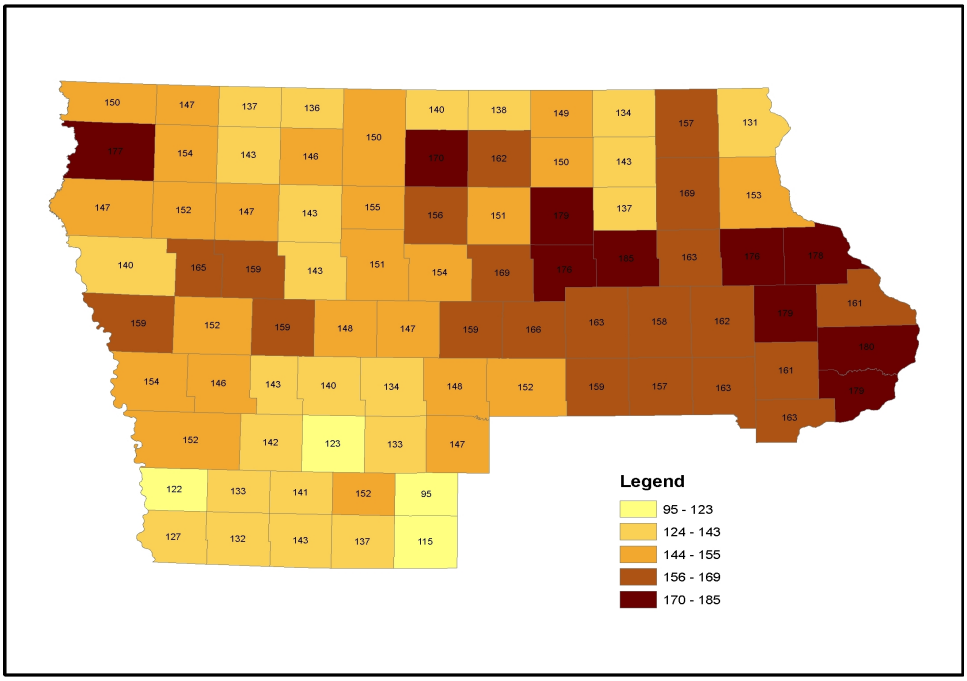


Figure 2.1 Cash Rental Rates, 2007 ($/acre/year)

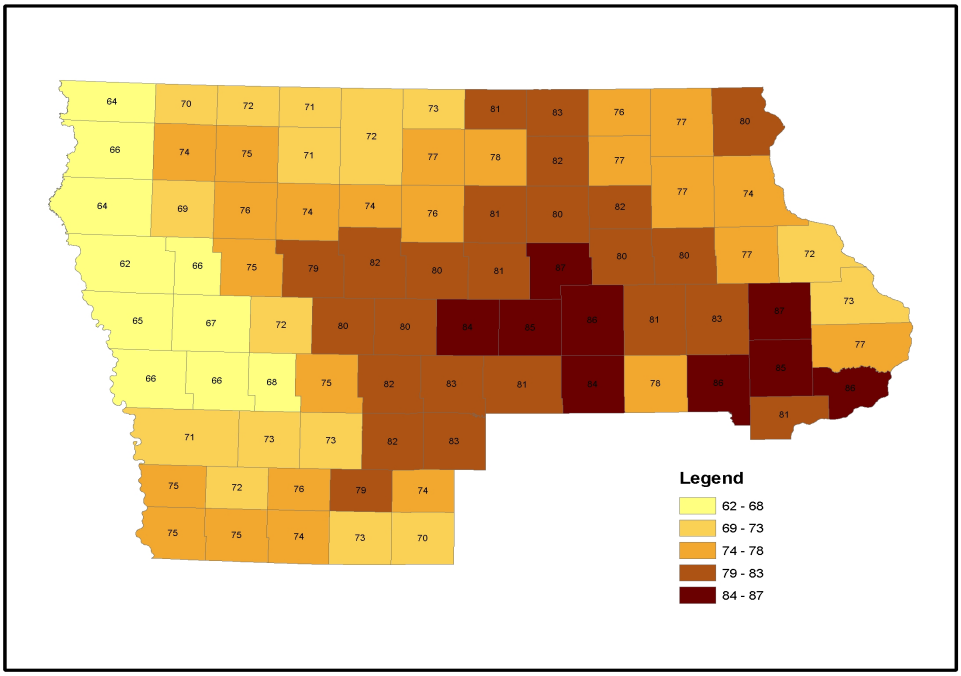


Figure 2.2 County Average Row Crop CSR Index

المنارة للاستشارات
www.manaraa.com

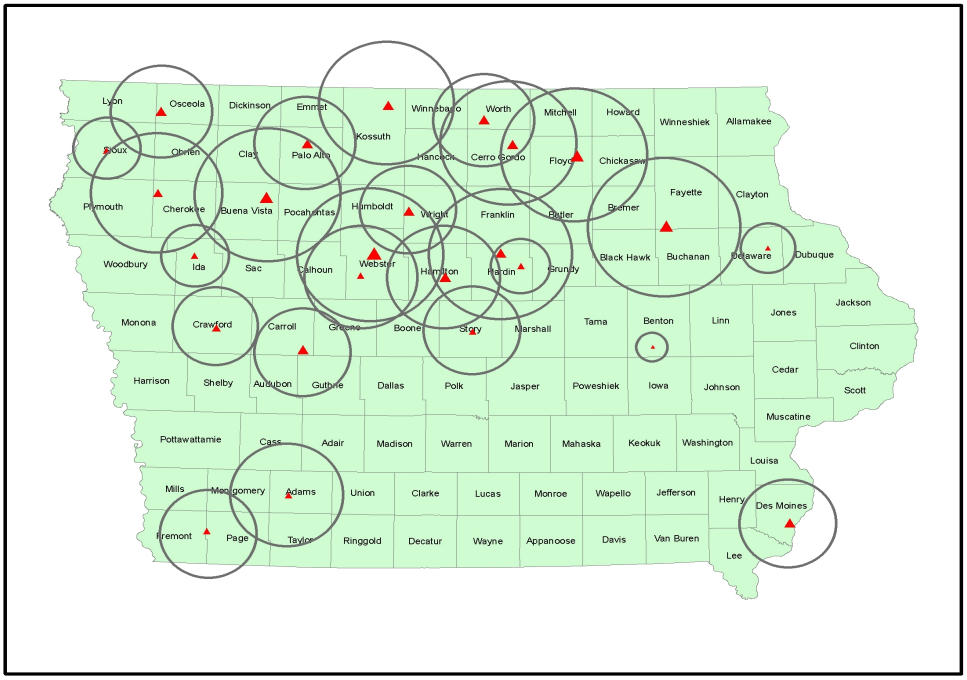


Figure 2.3 Ethanol Plants in Operation, 2007

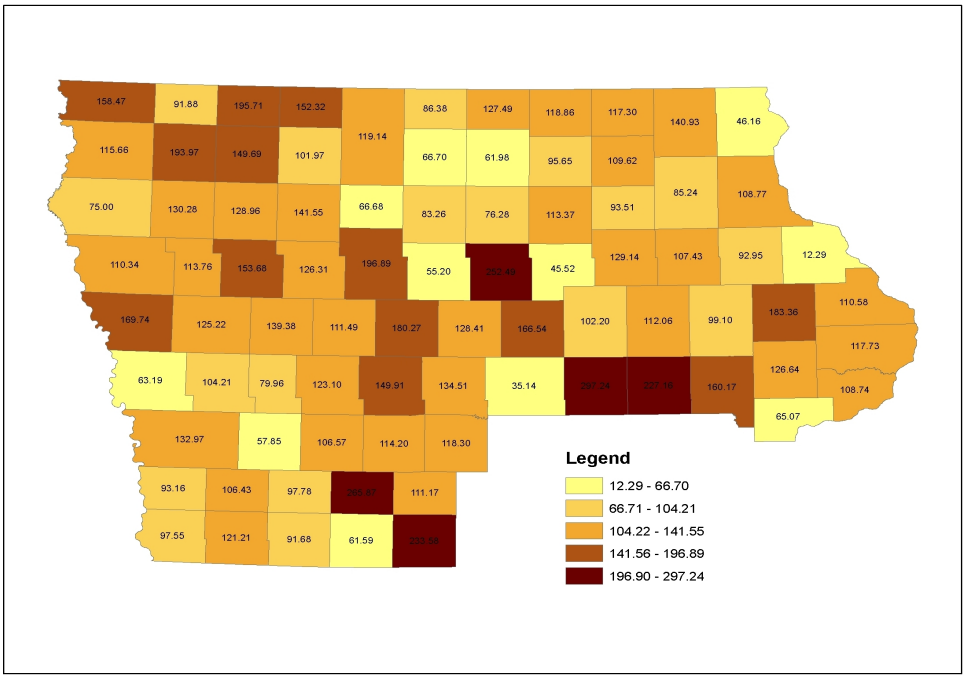


Figure 2.4 Long-run Effects (MG)

المنارة للاستشارات
www.manaraa.com

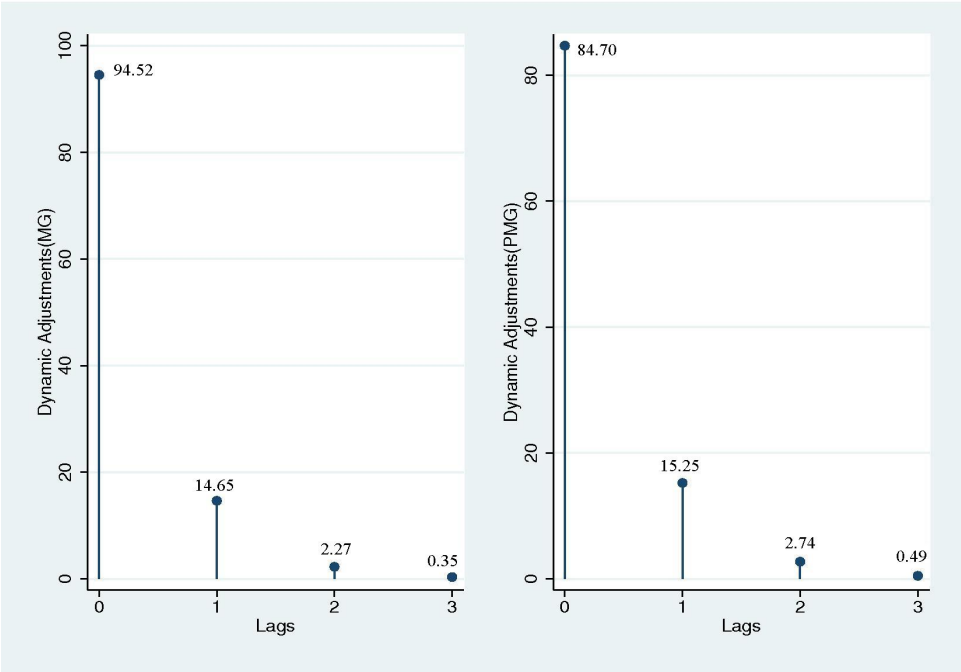


Figure 2.5 MG/PMG Estimates of Dynamic Adjustments

المنارة للاستشارات
www.manaraa.com

3. THE PLANTING REAL OPTION IN CASH RENT VALUATION

Abstract

After entering into a farmland rental contract in the fall, a tenant farmer has the flexibility over the spring crop choice and the input application level. Failure to account for these options will bias estimates of what farmers should pay to rent land. Applying contingent claims analysis methods, this study explicitly derives the option value function for these choices. Comparative statics with respect to the volatilities of underlying state variables and their correlations are derived and discussed. A multivariate Gaussian copula is employed to account for dependence among yields and prices. Monte Carlo simulation results show that the average cash rent valuation for the real option approach is 13.5% higher than that for the conventional net present value (NPV) method, in which the input intensity option is 0.47%. Crop planting sequence is shown to impact the real option value.

Key words: cash rent, Gaussian copula, Monte Carlo simulation, Ricardian rent.

المنارة للاستشارات

www.manaraa.com

Introduction

Cropland rental rates have adjusted substantially over the period 2005-08 (Edwards and Smith 2008). This has largely been due to price shifts arising from demand for corn as an ethanol plant feedstock. Landlords and tenants have needed to re-evaluate their willingness to pay and accept rents in this new environment. The goal of this paper is to provided a better understanding of willingness to pay for rented cropland.

In the United States, tenant farmers generally rent cropland in the fall to prepare for spring planting. Cash rent is an important feature of midwestern crop production. In Iowa, as an example, about 40% of cropland is rented under cash rental agreements. Our contention is that the fall to spring time gap is important for how cash renters value access to land as commodity prices can move substantially over this period. The standard cash rent calculation method suggested by farm management textbooks (e.g., Calkins and DiPietre 1983, p. 394; Olson 2004, p. 285; Kay, Edwards, and Duffy 2004, p. 359) is the so-called tenant's residual approach. The method is to derive a residual, or Ricardian rent, for land by deducting operating costs from crop revenue based on expected yields, prices, and operating expenses. After taking into account planting decisions faced by a farmer who chooses between corn and soybeans, the traditional net present value (NPV) method calculates the present value of expected corn cash flows and also the present value of expected soybeans cash flows. The maximum value of this pair of present values is then used to determine cash rent. The major drawback of the conventional NPV method as applied to cash rent valuation is that it ignores the option to choose what to plant. Thus, it underestimates what farmers should be willing to pay for rental land.

Like other investment decisions, farmer's production intentions with rented land share three distinct features of real options, as described in Dixit and Pindyck (1994). One is irreversibility. Once the crop has been planted, related sunk costs cannot be fully recovered. Another is uncertainty. Profit uncertainty is due to stochastic output, as well as time-varying input and output prices. The third feature is leeway in timing. After entering into a farmland rental agreement, a tenant farmer has an extensive margin flexibility to "switch" between corn

المنارة للاستشارات
www.manaraa.com

and soybeans for the next crop year. He also has an intensive margin flexibility concerning the level of inputs to apply at planting. We refer to the total value of these two real options as the planting real option in this study. And these options mature at the planting time.

The impacts of irreversibility, uncertainty and the choice of timing on investment project decisions and valuation have been widely recognized and applied to various investment problems in agriculture. For example, Tzouramani and Mattas (2004) employ the real option approach to better assess investment opportunities when compared with the NPV approach. Odening, Mußhoff, and Balmann (2005) calculate investment triggers and option values when accounting for the value of waiting for an investment in hog fattening in Germany. Luong and Tauer (2006) model Vietnamese coffee growers' entry and exit decisions as real options. Mußhoff and Hirschauer (2008) apply the dynamic programming and simulation methods to sales contracting decision problems facing German grain farmers. The most relevant application to our work is Marcus and Modest (1984). They applied continuous time option pricing methods to solve a farmer's optimal production decision problem. Crop futures prices are used as the stochastic state variables that characterize the uncertainty faced by farmers.

The value of a tenant farmer's potential planting flexibility, which should be reflected in cash rent determination, is largely driven by volatile input and output prices. Failure to account for option values will bias estimates of what farmers should pay to rent land. The literature on farmland cash rent determination is surprisingly limited and the embedded real option component is entirely ignored. Kurkalova, Burkart, and Secchi (2004), for example, estimate the cash rental rate as a function of the typical corn yield in the Upper Mississippi River Basin in 1997. Dhuyvetter and Kastens (2002) use an accounting approach to model cash rents. Lence and Mishra (2003) and Goodwin, Mishra, and Ortalo-Magné (2004) develop regressions of cash rents against crop revenues and government payments in order to better understand the role of government interventions. Du, Hennessy, and Edwards (2007) employ a variable profit function Ricardian rent approach to analyze the determinants of cash rents using Iowa county-level panel data. None of these seeks to model planting time flexibility.

Contrary to the traditional NPV method, in this study, we explicitly derive the value of

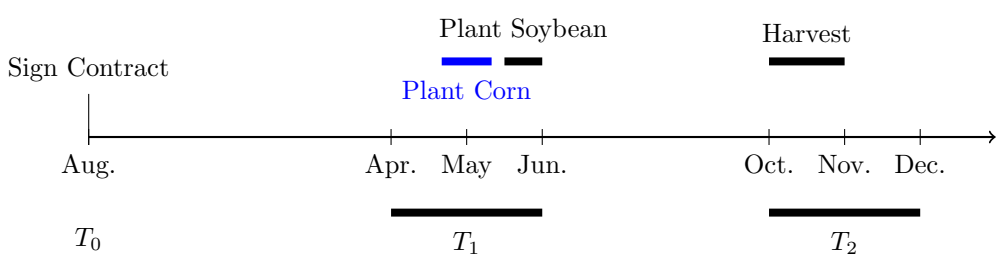
المنارة للاستشارات
www.manaraa.com

the switching and input intensity options. Using historical cash prices, as well as experimental production data, and employing a Gaussian copula to account for the multivariate dependence, we evaluate the option, i.e., flexibility, values by Monte Carlo methods. Our contributions to the literature on cash rent will be to identify the existence and importance of the planting option in cash rent determination.

The paper proceeds as follows. First, a conceptual model of real option valuation is developed. Comparative statics of the switching option with respect to volatilities and correlation of underlying state variables are derived and discussed. Second, an empirical Monte Carlo simulation method is described. Copula estimation and simulation methods for random input and output prices and crop yields are presented. The estimation focuses on the option's contribution to cash rent. The final section concludes with a brief discussion.

Conceptual Model

In Iowa, corn is typically planted between April 20 and May 10 each year. The best planting time for soybeans is from May 15 to June 1. Crops are harvested from October to November of the same year. After signing a farmland rental contract, typically in August the previous year, a tenant farmer makes planting and input choice decisions in April. When making planting decisions, farmers observe and use price information from the futures contracts expiring right after harvest time to formulate harvest price expectations. When deciding what can be paid for rented land, farmers will use futures prices to establish what they may plant, how intensively they will farm, and the value of what they will reap. On the Chicago Board of Trade (CBOT), the December contract for corn and the November contract for soybeans are the first available futures contracts after harvest time. The time line is as follows:



المنارة للاستشارات
www.manaraa.com

where T_0 is the time when a tenant farmer signs the farmland rental contract, T_1 is the time when the planting and input decisions are made, and T_2 is the harvest time. In addition, time $t \in [T_0, T_2]$ is the continuous time indicator.

NPV vs. Real Option Methods

The traditional NPV approach assumes that a tenant farmer makes the planting decision when agreeing on the cash rent. When corn and soybeans are the crops that may be chosen, a tenant farmer compares expected corn profit, $E_t(\pi_C) = E_t[E_{T_1}(\pi_C)]$, with that of soybeans, $E_t(\pi_S) = E_t[E_{T_1}(\pi_S)]$. $E_t[\cdot]$ denotes the expectation operator conditional on information available at time t under the risk-neutral measure. Expectations $E_{T_1}(\pi_C)$ and $E_{T_1}(\pi_S)$ are expected harvest time corn and soybean profits at planting time T_1. The present value of $E_t(\pi_C)$ and $E_t(\pi_S)$ are obtained from discounting the expected profits back to the decision-making time t by risk-free rate r. In the standard NPV approach to rent determination, the planting choice is implicitly assumed to have been made with certainty by time t where $t < T_1$.[1] A tenant farmer plants the crop with higher present value of expected profit, which is also the amount of cash rent paid out to the landowner and is calculated as

$$V_1 = e^{-r(T_2-t)} \max\{E_t(\pi_C), E_t(\pi_S)\} \quad \text{(Traditional approach)} \tag{3.1}$$

Contrast this approach with the real option method, in which a tenant farmer is assumed to have the flexibility to switch between corn and soybeans until the planting time. The corresponding cash rent valuation taking into account the real option value is

$$V_2 = e^{-r(T_2-t)} E_t[\max(\pi_C, \pi_S)] \qquad \text{(Real option approach)} \tag{3.2}$$

Here, the planting choice is not made until time T_1. It's readily shown that $V_1 \leq V_2$ is true by Jensen's inequality. Also, at maturity, the real option payoff is

$$E_{T_1}\{\max(\pi_C, \pi_S)\} - \max\{E_{T_1}(\pi_C), E_{T_1}(\pi_S)\} \tag{3.3}$$

[1] The traditional approach also ignores intensive margin planting time flexibility in input use. It identifies an expected profit at T_0, not allowing for flexibility in waiting for knowledge of $F_{T_1,i}$, $i \in \{C, S\}$ to choose input levels for each given crop (Oi 1961).

المنارة للاستشارات
www.manaraa.com

with the strike price being $\max\{E_{T_1}(\pi_C), E_{T_1}(\pi_S)\}$. In general, the smaller the difference between corn and soybean expected profits, the higher the real option premium will be. The switching option will have little value if the profit from one crop is almost certain to dominate those from all other crops.

In this study, the planting option is further decomposed to include the switching option described above and the input intensity option. We only consider value of the input intensity option embedded in corn profit, in which the nitrogen price is explicitly included. The corn profit taking into account the input intensity option value is $V_3 = e^{-r(T_2-t)}E_t(\pi_{C,N^*})$, while $V_4 = e^{-r(T_2-t)}E_t(\pi_{C,N})$ represents the traditional corn profit. Nitrogen application level N^* in V_3 is determined by expected price information at planting time T_1. The level of N in V_4 is decided at T_0, the sign-up time for rental contracts. Since N^* is conditioned on the actual nitrogen price and a more informed signal on harvest price for corn, it follows that $V_3 \geq V_4$ and a budget approach that assumes the nitrogen choice at contract sign-up will undervalue rent.

Real Option Valuation

The option of choosing between corn and soybeans is equivalent to an option to exchange one risky asset for another. Values of the crops are assumed to be the two assets to be exchanged and can be derived using contingent claim analysis methods as developed in Black and Scholes (1973), Merton (1973, 1977), and Dixit and Pindyck (1994).

Write the time t expected corn and soybean prices at harvest time T_2 as $F_{t,C}$ and $F_{t,S}$, and write the time t nitrogen fertilizer price at planting time T_1 as $F_{t,N}$. To promote precise notation, futures maturity date T_2 has been suppressed. All are held to follow geometric Brownian motions as

$$\frac{dF_{t,i}}{F_{t,i}} = \mu_{F_{t,i}}dt + \sigma_{F_{t,i}}dz_i \quad i \in \{C, S, N\}. \tag{3.4}$$

over $t \in [T_0, T_1]$ where $\mu_{F_{t,i}}$ is the instantaneous expected rate of return, $\sigma^2_{F_{t,i}}$ is the volatility of the expected price, and dz_i follows a Wiener process. In addition, ρ_{CS}, ρ_{CN}, and ρ_{SN} are used in this study to denote the instantaneous correlations between the Wiener processes dz_C

المنارة للاستشارات
www.manaraa.com

and dz_S, dz_C and dz_N, dz_S and dz_N, respectively.

The soybean futures price, $F_{t,S}$, is considered to be the only stochastic state variable determining the value of soybean profit, $V_t^S(F_{t,S})$, at time t. This is because nitrogen is seldom applied on soybeans. The corn and nitrogen fertilizer futures prices, $F_{t,C}$ and $F_{t,N}$, are considered to be the stochastic state variables driving the changes of corn crop value. Following Marcus and Modest (1984), it is shown in the appendix that the corn and soybean value functions, $V_t^C(\cdot)$ and $V_t^S(\cdot)$, are determined by time, futures prices, price volatilities and correlations, as well as production technology. Cobb-Douglas cost functions are assumed to represent the corn and soybean production technologies with parameters δ_C, δ_S, and δ_N.

Following Margrabe (1978), in the appendix the value of the switching option is shown as

$$\begin{aligned}
\Pi\left(V^C, V^S, t\right) &= V_t^C \Phi(d_1) - V_t^S \Phi(d_2) \geq 0 \\
d_1 &= \frac{\ln(V_t^C/V_t^S) + \frac{1}{2}\sigma_V^2 (T_1 - t)}{\sigma_V \sqrt{T_1 - t}}; \quad d_2 = d_1 - \sigma_V \sqrt{T_1 - t} \\
\sigma_V^2 &= \delta_C^2 \sigma_{F_{t,C}}^2 + \delta_S^2 \sigma_{F_{t,S}}^2 + \delta_N^2 \sigma_{F_{t,N}}^2 \\
&\quad + 2\delta_C \delta_N \sigma_{F_{t,C}} \sigma_{F_{t,N}} \rho_{CN} - 2\delta_C \delta_S \sigma_{F_{t,C}} \sigma_{F_{t,S}} \rho_{CS} - 2\delta_S \delta_N \sigma_{F_{t,S}} \sigma_{F_{t,N}} \rho_{SN} \\
&= \begin{pmatrix} \delta_C & \delta_S & -\delta_N \end{pmatrix} \begin{pmatrix} \sigma_{F_{t,C}}^2 & \sigma_{F_{t,C},F_{t,S}} & \sigma_{F_{t,C},F_{t,N}} \\ \sigma_{F_{t,C},F_{t,S}} & \sigma_{F_{t,S}}^2 & \sigma_{F_{t,S},F_{t,N}} \\ \sigma_{F_{t,C},F_{t,N}} & \sigma_{F_{t,S},F_{t,N}} & \sigma_{F_{t,N}}^2 \end{pmatrix} \begin{pmatrix} \delta_C \\ \delta_S \\ -\delta_N \end{pmatrix} \\
&\geq 0 \qquad (3.5)
\end{aligned}$$

where $\sigma_{F_{t,C},F_{t,S}} = \sigma_{F_{t,C}} \sigma_{F_{t,S}} \rho_{CS}$ is the covariance between $F_{t,C}$ and $F_{t,S}$, and $\sigma_{F_{t,C},F_{t,N}}$ as well as $\sigma_{F_{t,S},F_{t,N}}$ are similarly defined. The cdf of standard normal distribution is $\Phi(\cdot)$.

Comparative Statics of the Switching Option

The comparative statics of the switching option with respect to volatilities of the underlying price variables, also called the option Vegas, measure how much the option price would change when the volatility of the underlying state variable changes. Derivations in the appendix indicate that the effects of changes in the volatility of the state variables, $\sigma_{F_{t,C}}$, $\sigma_{F_{t,S}}$, and $\sigma_{F_{t,N}}$, on the option value are, in general, ambiguous. The standard result that an increase in

المنارة للاستشارات
www.manaraa.com

the volatility of the underlying state variable increases the option value doesn't hold here. The situation is more complicated because overall volatility σ_V^2 depends on state variable volatilities and correlations, as well as technology parameters $\delta_i,\ i \in \{C, S, N\}$.

The partial derivatives of the switching option with respect to correlation between underlying price variables are also derived in the appendix. The results show that given price volatilities $\sigma_{F_{t,C}}$ and $\sigma_{F_{t,S}}$, a higher correlation between corn and soybean prices leads to a lower option value. That is, a tenant farmer is less likely to change crop choice and thus the switching option has less value to him when crop values tend to move up and down together. Also, given corn and nitrogen price volatilities, $\sigma_{F_{t,C}}$ and $\sigma_{F_{t,N}}$, a higher correlation between the input and output prices, ρ_{CN}, leads to a more stabilized value of the corn crop. This in turn reduces the value of the option to exchange the crops as corn profit is less likely to be deep in the money when compared with soybean profit. Similarly, a higher option value is associated with an increase in ρ_{SN} because changes in the same direction of soybean and nitrogen prices encourage tenant farmers to switch the planting choice.

Empirical Model

Using local corn, soybean, and nitrogen fertilizer cash prices, and crop production data collected from controlled experiments, we apply Monte Carlo methods to value the planting and input intensity options. Income uncertainty faced by a tenant farmer comes from three sets of random variables. These are output prices, input prices, and crop yields.[2] A fundamental feature of these random variables is that they are correlated. For example, the corn price is correlated with the soybean price, the nitrogen fertilizer price, and also corn and soybean yields. All prices and yields are treated as random variables in our simulation. And we explicitly model their dependence using a multivariate Gaussian copula.

Under the assumption of risk neutrality, the Monte Carlo method involves evaluating the cash rent implied by the NPV and real option approaches at planting time T_1, then discounting

[2] As no additional insights would be gained from including yield uncertainty in the conceptual model, we omitted it. We could readily have done so in the manner of Marcus and Modest (1986). The easiest way to do so is to assume a log-normal yield distribution. But that is not realistic.

المنارة للاستشارات
www.manaraa.com

back at the risk-free rate as given by V_1 in (3.1) and V_2 in (3.2). The corn and soybeans profits are assumed to be

$$\pi_{T_1,C} = P_{T_1,C} y_{T_1,C} - P_{T_1,N} N - K_C^{'} \qquad \pi_{T_1,S} = P_{T_1,S} y_{T_1,S} - K_S \tag{3.6}$$

where $P_{T_1,i}$, $i \in \{C, S\}$ denote the planting time T_1 expected local harvest prices, and $P_{T_1,N}$ denotes price of nitrogen fertilizer at time T_1. Amount $K_C^{'}$ is the corn production cost excluding the cost of nitrogen fertilizer,[3] while K_S is the soybean production cost. Symbol N denotes the quantity of nitrogen fertilizer input and $y_{T_1,i}$, $i \in \{C, S\}$ are expected yields of corn and soybeans, respectively.

The Monte Carlo simulation consists of the following steps:

(a) Based on estimated parameters, simulate the underlying random variables, i.e., generate n prices of $P_{T_1,C}, P_{T_1,S}$, and $P_{T_1,N}$; generate corn and soybean yields forecasts $y_{T_1,C}$ and $y_{T_1,S}$ at planting time T_1.

(b) Applying Iowa annual crop production budget data (Duffy and Smith 1979-2008) for $K_C^{'}$ and K_S and generated quantities in step (a), get n terminal corn and soybean profits, $\pi^i_{T_1,C}, \pi^i_{T_1,S}$, $i \in \{1, 2, ..., n\}$;

(c) Take the average of the discounted final option values under the NPV and real option approaches to obtain an estimate of these values at time t as

$$\begin{aligned} \hat{V_1}(t) &= e^{-r_t(T_2-t)} \max\left\{\frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,C}), \frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,S})\right\} \\ \hat{V_2}(t) &= e^{-r_t(T_2-t)} \frac{1}{n}\sum_{i=1}^{n} \max\left(\pi^i_{T_1,C}, \pi^i_{T_1,S}\right) \end{aligned} \tag{3.7}$$

In addition, $\hat{V_3}(t) = e^{-r_t(T_2-t)}\left\{\frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,C,N^*})\right\}$ is the corn profit at planting time including value of the input intensity option where N^* is conditioned on planting time information. By contrast, $\hat{V_4}(t) = e^{-r_t(T_2-t)}\left\{\frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,C,N})\right\}$ denotes the traditional corn profit where N is conditioned on sign-up time information.

In step (a) variations of prices and yields are randomly drawn from a 5-dimension multivariate distribution, which is defined by the five marginal distributions of yield and price

[3] It is not quite the same as K_C of equation (A-1), which includes the cost of nitrogen fertilizer.

المنارة للاستشارات
www.manaraa.com

variations, as well as a multivariate Gaussian copula. The expected corn and soybean yields are obtained from OLS regressions of experimental data after taking into account rotation effects. The copula estimation and simulation method for yield and price variables are now discussed in greater detail.

Copula Method

Due in part to its flexibility, the Copula method has recently become a significant tool for modeling the dependence between two or more variables. For a non-normal multivariate joint distribution, the dependence structure captured by a copula function is more informative than linear correlation. Nelsen (1999) provide detailed statistical and mathematical introductions to copula methods, while Cherubini, Luciano, and Vecchiato (2004) presents applications in empirical finance and asset pricing. Copula based approaches are applied to model the correlations between crop prices and yields when studying farm and revenue insurance contract in Zhu, Ghosh, and Goodwin (2008) and in Tejeda and Goodwin (2008). Vedenov (2008) compares performance of the copula method with other techniques on modeling the joint distribution of farm and county-level corn yields in Iowa.

By Sklar's theorem (Sklar, 1959), any h dimensional joint distribution function may be decomposed into its h marginal distributions, and a h-copula, which completely describes the dependence between the h random variables. Let $X_1, ..., X_h$ be continuous random variables with distribution function $F(x_1, ..., x_h)$ and marginal distribution functions $F_1, ..., F_h$, correspondingly. A h-copula is a mapping from the individual distribution functions to the joint distribution function as

$$F(x_1, ..., x_h) = C\left(F_1(x_1), ..., F_h(x_h)\right), \quad \text{for } (x_1, ..., x_h) \in [-\infty, \infty]^h. \tag{3.8}$$

Conversely, if C is an h-copula function and $F_1, ..., F_h$ are marginal distribution functions, the function F defined in (3.8) is a h-dimension distribution function with margins $F_1, ..., F_h$. And the corresponding copula can be constructed as

$$C(u_1, ..., u_h) = F\left(F_1^{-1}(u_1), ..., F_h^{-1}(u_h)\right), \tag{3.9}$$

المنارة للاستشارات
www.manaraa.com

where F_i^{-1} is the inverse distribution function, i.e., $F_i^{-1} = \sup\{x_i | F_i(x_i) \leq u_i\}$, for $i \in \{1, ..., h\}$. That is, a copula is a multivariate distribution function with Uniform$(0, 1)$ univariate marginal distributions.

The Gaussian copula is one of the most frequently used parametric families of copula functions. The multivariate Gaussian copula (MGC) takes the form of

$$C^{\text{Ga}}(u_1, ..., u_h; R) = \Phi(F_1^{-1}(u_1), F_2^{-1}(u_2), ..., F_h^{-1}(u_h); R) \tag{3.10}$$

where R is a symmetric, positive definite matrix with diagonal elements of 1's and $\Phi(\cdot)$ is the multivariate standard normal distribution with correlation matrix R. F_i^{-1} represents the inverse of the univariate distribution F_i. The copula is not constrained by the choice of marginal distributions, which may take any form of continuous distribution function.

Parameter estimation can proceed as follows. Let β be the vector of marginal distribution parameters and ρ be the vector of copula's dispersion parameters, i.e., the elements of correlation matrix R. Given m observations from a multivariate distribution, the parameter vector to be estimated is $\theta = (\beta', \rho')'$. The corresponding log-likelihood function can be specified as (Yan 2008):

$$\begin{aligned} l(\theta) &= \sum_{i=1}^{m} \log c\{F_1(X_{i1}; \beta), ..., F_h(X_{ih}; \beta); \rho\} + \sum_{i=1}^{m} \sum_{j=1}^{h} \log f_i(X_{ij}; \beta); \\ c(u_1, ..., u_h) &= \frac{f[F_1^{-1}(u_1), ..., F_h^{-1}(u_h)]}{\prod_{i=1}^{h} f_i[F_i^{-1}(u_i)]} \end{aligned} \tag{3.11}$$

The maximum likelihood (ML) estimator of θ is $\hat{\theta} = \underset{\theta \in \Theta}{\text{argmax}}\, l(\theta)$.

In this study, there are 20 parameters to estimate, including 10 dispersion parameters for the 5-dimension MGC, $\rho_i,\ i \in \{1, ..., 10\}$, as in

$$R = \begin{pmatrix} 1 & \rho_1 & \rho_2 & \rho_3 & \rho_4 \\ \rho_1 & 1 & \rho_5 & \rho_6 & \rho_7 \\ \rho_2 & \rho_5 & 1 & \rho_8 & \rho_9 \\ \rho_3 & \rho_6 & \rho_8 & 1 & \rho_{10} \\ \rho_4 & \rho_7 & \rho_9 & \rho_{10} & 1 \end{pmatrix}$$

المنارة للاستشارات
www.manaraa.com

and 10 parameters for the five corresponding marginal univariate distributions. To reduce the computational difficulty of the optimization problem, we apply the inference functions for margins (IFM) method of Joe (1997, Ch. 10; 2005) as used in, e.g., Zhu, Ghosh, and Goodwin (2008) and Tejeda and Goodwin (2008), which consists of two estimation steps:

(a) estimate the marginal distribution parameters β by

$$\hat{\beta}_{\text{IFM}} = \underset{\beta}{\operatorname{argmax}} \sum_{i=1}^{m} \sum_{j=1}^{h} \log f_i(X_{ij}; \beta) \tag{3.12}$$

This is equivalent to an ML estimation for parameters β_j for each marginal distribution $F_j, j = 1, ..., h.$ as

$$\hat{\beta}_{j,\text{IFM}} = \underset{\beta_j}{\operatorname{argmax}} \sum_{i=1}^{m} \log f_i(X_{ij}; \beta_j). \tag{3.13}$$

(b) then estimates the copula parameters ρ given $\hat{\beta}_{j,\text{IFM}}$ by

$$\hat{\alpha}_{\text{IFM}} = \underset{\alpha}{\operatorname{argmax}} \sum_{i=1}^{m} \log c \left(F_1(X_{i1}; \hat{\beta}_{j,\text{IFM}}), ..., F_h(X_{ih}; \hat{\beta}_{j,\text{IFM}}); \rho \right). \tag{3.14}$$

Data and Estimation Results

In this study, we model the corn, soybean, and nitrogen price variations, P_C, P_S, and P_N, jointly with the distributions of corn and soybean yields, y_C and y_S, by employing a 5-dimension MGC and five univariate distributions. The marginal distributions are specified as normal for variations in log of prices and beta for yield variations.

Corn and soybean yields can differ by soil quality, climate, and many other natural factors. In this study, controlled experimental production data at one location enable us to model corn yield as a function of time and the input quantity of nitrogen fertilizer, and also soybean yield as a function of time only. The appropriate distribution for yield variation is still subject to debate. Just and Weninger (1999) favor for normally distributed crop yields, while Ker and Goodwin (2000) prefer non-parametric yield density estimation. Ker and Coble (2003) point out that sufficient yield data are lacking to accept or reject various reasonable parametric distribution models. The beta distribution is popular in the empirical literature because of the common view that crop yield distributions can be skewed (Nelson and Preckel 1989), which is also the reason why we choose the beta distribution to model yield variations. The yield

المنارة للاستشارات
www.manaraa.com

variations are OLS regression residuals for corn and soybean yield equations, to be explained below.

In this study, crop production data are from controlled experiments conducted at Iowa State University's Research and Demonstration Farm located in Floyd County, Iowa, from 1979 to 2003 (Mallarino, Ortiz-Torres, and Pecinovsky 2004). The data are collected under five rotations, $\langle C \rangle, \langle CS \rangle, \langle CCS \rangle, \langle CCCS \rangle$, and $\langle S \rangle$, where $\langle CCCS \rangle$ is to be read as the corn-corn-corn-soybeans rotation. Four nitrogen levels, 0 lb./ac., 80 lb./ac., 160 lb./ac., and 240 lb./ac. were applied. Each combination of rotation and nitrogen level are replicated three times in a year. So for each year there are $3 \times 4 \times (1 + 1 + 2 + 3) = 84$ observations for corn and $3 \times 4 \times (1 + 1 + 1) = 36$ observations for soybeans. There are five combinations of four-year corn sequences observed in our data, in which the last crop is corn, $\langle SCSC \rangle$, $\langle CCSC \rangle$, $\langle CSCC \rangle$, $\langle SCCC \rangle$, and $\langle CCCC \rangle$, while we observe three sequences with soybeans the last crop, $\langle CSCS \rangle$, $\langle SCCS \rangle$, and $\langle CCCS \rangle$.

The corn yield model is specified as

$$y_{t,C} = \alpha_C + \beta_C t + \beta_N N + \beta_{N^2} N^2 + \gamma_C D + \varepsilon_{t,C} \tag{3.15}$$

where N is the nitrogen application level, $t \in \{1, 2, ..., T\}$ $(T = 25)$ the time, and $\varepsilon_{t,C}$ the random variation. The D is a dummy variable with value 1 when corn is in the sequence of $\langle CC \rangle$ and 0 when corn is planted after soybeans. Using the same data set, Hennessy (2006) find empirical support for one year memory of corn, which indicates that only the $\langle CC \rangle$ and $\langle CS \rangle$ sequences are distinguishable from each other. Thus D is the only indicator variable included in (3.15). We combine the data for the crop sequences for corn of $\langle SCSC \rangle$ and $\langle CCSC \rangle$ and those of $\langle CSCC \rangle$, $\langle SCCC \rangle$, and $\langle CCCC \rangle$ together to apply the OLS regression model described in (3.15). Soybean production is found to have two-year memory in Hennessy (2006). So there is no distinction between the yield effects of $\langle SCCS \rangle$ and $\langle CCCS \rangle$. The soybean yield model is then

$$y_{t,S} = \alpha_S + \beta_S t + \gamma_S E + \varepsilon_{t,S} \tag{3.16}$$

Here, dummy variable E represents the sequence $\langle CSCS \rangle$ and $\varepsilon_{t,S}$ represents the yield varia-

المنارة للاستشارات
www.manaraa.com

tion. The estimation results are presented in table 3.1. The regression results for corn yield indicate that the yield enhancement effect of corn after soybean relative to corn after corn is approximately 29.12 bu./ac. And the implied maximum nitrogen level is 212.5 lb./ac., which is in the reasonable range.

Crop yield, y, is typically assumed to follow a beta distribution with the probability density function in the form of

$$f(y) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times \frac{(y-y_{min})^{\alpha-1}(y_{max}-y)^{\beta-1}}{y_{max}^{\alpha+\beta-1}},$$

where α and β are shape parameters and y_{max} and y_{min} are maximum and minimum possible yields (Nelson and Preckel 1989). These are the four parameters to estimate. But, as is standard, the upper and lower supports are imposed. We will estimate these distributions, but will use the regression residuals from (3.15) and (3.16), $\hat{\varepsilon}_{t,i}$, $i \in \{C, S\}$, and not yields. The normalized yield variation for year t of crop i is then calculated as $\tilde{\varepsilon}_{t,i} = 1 + \frac{\hat{\varepsilon}_{t,i}}{\hat{y}_{t,i}}$ where $\hat{y}_{t,i}$ is the corresponding fitted value of the yield regression. The vector $\tilde{\varepsilon}_i$ has the dimension of $[T \times 1]$ with mean and standard deviation denoted by $\bar{\varepsilon}_i$ and $\sigma_{\tilde{\varepsilon}_i}$, respectively.

The upper support of $\tilde{\varepsilon}_i$ is imposed as the value of three standard deviations from the mean, i.e., $\tilde{\varepsilon}_{i,max} = \bar{\varepsilon}_i + 3\sigma_{\tilde{\varepsilon}_i}$, while the lower supports $\tilde{\varepsilon}_{i,min}$ is imposed as 0. The normalized yield residual $\tilde{\varepsilon}_i$ is then transformed to a standard beta random variable $\tilde{\xi}$ as

$$\tilde{\xi}_{t,i} = \frac{\tilde{\varepsilon}_{t,i} - \tilde{\varepsilon}_{i,min}}{\tilde{\varepsilon}_{i,max} - \tilde{\varepsilon}_{i,min}} \tag{3.17}$$

In addition, $\tilde{\xi}_i$ is truncated to be in the range of $[0, 1]$ as $\tilde{\xi}_{t,i} = 1$ for $\tilde{\varepsilon}_{t,i} > \tilde{\varepsilon}_{i,\max}$. The truncation is very unlikely to be applied given the range of three standard deviations. The constructed beta distribution has two shape parameters to be estimated following the IFM estimation method in (3.13). The estimated shape parameters of corn and soybean yields are presented in table 3.2, which indicate that both distributions are left skewed.

In order to match with the crop yields specifically estimated from experimental data for Floyd County, Iowa, monthly average (November for corn and October for soybeans) cash prices quoted in North Central Iowa from 1979 to 2003 are also used. The interval is chosen to match the available yield data. The data are reported in the "Daily Historical Grain Report"

المنارة للاستشارات
www.manaraa.com

by the Iowa Department of Agriculture and Land Stewardship.[4] The difference between the logarithm of prices in two consecutive years, $\tilde{\zeta}_{t,i} = \log(P_{t,i}) - \log(P_{t-1,i})$, is assumed to be normally distributed. So the crop price is assumed to be distributed as log-normal, which is a typical assumption in the literature. The mean and variance distribution parameters are estimated following the IFM method in (3.13) and the results are given in table 3.2. Similarly, nitrogen fertilizer price is also assumed to be log-normally distributed, the data for which are obtained from "Estimated Costs of Crop Production in Iowa" (Duffy and Smith 1979-2008). The estimated parameters are also presented in table 3.2. Finally, price and yield variations, $\tilde{\xi}_C, \tilde{\xi}_S, \tilde{\zeta}_C, \tilde{\zeta}_S$, and $\tilde{\zeta}_N$, are used for the estimation of 5-dimension MGC's dispersion parameters ρ_i, $i \in \{1, ..., 10\}$. The results are given in the second part of table 3.2, and appear to be reasonable.

The Monte Carlo Simulation

Jointly simulating $\tilde{\xi}_C, \tilde{\xi}_S, \tilde{\zeta}_C, \tilde{\zeta}_S$, and $\tilde{\zeta}_N$ from the multivariate distribution involves generating random variates from the estimated MGC and transforming the random variates to univariate random variables. Specifically, as described in Cherubini, Luciano, and Vecchiato (2004, Ch. 6) the steps for generating one set of random variates are: (a) Simulate h independent random variates $z = (z_1, z_2, ..., z_h)'$ from the standard normal distribution $N(0, 1)$. Note that h is the dimension of the MGC and the multivariate distribution. (b) Generate $v = Az$ where A is the Cholesky Decomposition of the estimated MGC dispersion matrix $\hat{R}$; (c) Set $u^j = \Phi(v^j), j = 1, 2, ..., h$ where Φ denotes the univariate $N(0, 1)$ distribution function; (d) Set $x^j = F_j^{-1}(u^j), j = 1, 2, ..., h$ where F_j^{-1} denotes the inverse of the jth marginal cdf. Repeating the above procedure, we may obtain n (=5,000 in this study) realizations from the multivariate distribution of yield and price variations.

There are two sets of prices we need to simulate. One is the expected planting time prices for corn and nitrogen of year t, $\tilde{P}_{t,T_1,l}$, $l \in \{C, N\}$, which is used to determine the optimal

[4]The data are obtained from http://www.agriculture.state.ia.us/agMarketing/, last visited 10/12/2008.

المنارة للاستشارات
www.manaraa.com

nitrogen level N^* following

$$N^* = \left(\tilde{P}_{t,T_1,N} - \hat{\beta}_N \tilde{P}_{t,T_1,C}\right) / 2\hat{\beta}_{N^2} \tilde{P}_{t,T_1,C} \tag{3.18}$$

The other is expected local harvest prices at planting time of year t, $\tilde{P}_{t,T_2,l}$, $l \in \{C, S, N\}$, which are used in equation (3.6) to compute the expected corn and soybean profits.

Notice that we estimate the marginal distributions of log of harvest time prices as Normal$(\hat{\mu}_l, \hat{\sigma}_l^2)$, where $\hat{\mu}_l$ and $\hat{\sigma}_l^2$ are estimated mean and variance parameters for commodity l. In Iowa, the crop planting time of year t is approximately half a year before (after) the harvest time of year t $(t-1)$. Thus we have (Hull 2002, p. 228)

$$\begin{aligned} \ln(\tilde{P}_{t,T_1,l}) - \ln(\tilde{P}_{t-1,T_2,l}) &\sim \phi\left[\frac{1}{2}(\hat{\mu}_l - \frac{\hat{\sigma}_l^2}{2}), \frac{1}{2}\hat{\sigma}_l^2\right] \\ \ln(\tilde{P}_{t,T_2,l}) - \ln(\tilde{P}_{t,T_1,l}) &\sim \phi\left[\frac{1}{2}(\hat{\mu}_l - \frac{\hat{\sigma}_l^2}{2}), \frac{1}{2}\hat{\sigma}_l^2\right] \end{aligned} \tag{3.19}$$

Here, the normal probability density function (pdf) defined in equation (3.19) is the distribution we need to draw from to obtain random variates of the two sets of prices. So the corresponding normal cdf is the marginal function applied in the step (d) of the Monte Carlo simulation procedure. The prices are then transformed as

$$\begin{aligned} \tilde{P}_{t,T_1,l} &= \exp\left(\tilde{\zeta}_{t,T_1,l} + \log(P_{t-1,T_2,l})\right) \\ \tilde{P}_{t,T_2,l} &= \exp\left(\tilde{\zeta}_{t,T_2,l} + \log(P_{t,T_1,l})\right) \end{aligned} \tag{3.20}$$

where $\tilde{\zeta}_{t,T_1,l}$ and $\tilde{\zeta}_{t,T_2,l}$ are two sets of random variates generated from the steps (a) and (b) described above. Expression $\log(P_{t,T_1,l})$ appears twice in (3.19) to ensure the planting and harvest time prices are generated on the same random walk path.

The imputed optimal nitrogen level defined in equation (3.18), N^* is applied to corn yield regression model (3.15) to obtain the corresponding corn yield forecast at year t, $\hat{y}_{t,C}$. Similarly, we get soybean yield forecast, $\hat{y}_{t,S}$, from regression equation (3.16). The generated random variates $\tilde{\xi}_C$ and $\tilde{\xi}_S$ are transformed to yield variable as

$$\tilde{y}_{t,i} = \hat{y}_{t,i} * \tilde{\varepsilon}_{t,i} = \hat{y}_{t,i} * \left(\tilde{\xi}_i * (\tilde{\varepsilon}_{i,\max} - \tilde{\varepsilon}_{i,\min}) + \tilde{\varepsilon}_{i,\min}\right) \tag{3.21}$$

المنارة للاستشارات
www.manaraa.com

We consider the cases when the prior year crop was corn. Given simulated input, output prices, optimal nitrogen application level, and yield realizations, we get expected revenues from corn and soybeans at planting time T_1. The corn and soybean profits are then obtained by subtracting expected crop production costs from simulated revenues. Iowa annual crop production cost budget data (Duffy and Smith 1979-2008) are used for approximation of the production costs excluding cash rent costs. Then $\hat{V}_1(t)$ and $\hat{V}_2(t)$ in (3.7) are calculated. To quantify the value of the real option embedded in cash rent valuation, we define $\widehat{\%\Pi_1} = \left(\frac{\hat{V}_2(t)}{\hat{V}_1(t)} - 1\right) \times 100\%$ as the relative percentage of the planting option value in terms of $\hat{V}_1(t)$, where $\hat{V}_1(t)$ is the amount of cash rent determined by the traditional NPV method. The simulated cash rents evaluated by the NPV and real option methods and the relative real option value from 1995 to 2008 are presented in table 3.3. In terms of the input intensity option, the values of $\hat{V}_3(t)$ and $\hat{V}_4(t)$ are calculated as well as the relative percentage of the option value in terms of $\hat{V}_4(t)$, $\widehat{\%\Pi_2} = \left(\frac{\hat{V}_3(t)}{\hat{V}_4(t)} - 1\right) \times 100\%$.

From the simulation results, the average cash rent evaluated by the real option approach is about 13.5% higher than that of the traditional NPV method, in which the input intensity option is about 0.47%. As corn and soybean profits converge, i.e., corn is planted in about 50% of all simulation draws, the option value increases with a maximum value of 22.14% in 2002. When the profit of one crop dominates the other, the switching option is not as valuable. This was the case in 2004 and 2006 where in each case the option premium was less than 5% for our simulation context.

Furthermore, to value the embedded real option in cash rent for 2008, we fix the nitrogen fertilizer price as of August 2007 at \$0.31/lb, corn production costs at \$175.15, and soybean production costs at \$124.16 from the 2007 Iowa crop production budget (Duffy and Smith 2007). The corn price is assumed to vary from \$3 to \$6 and the soybean price is assumed to be in the range of \$6 to \$15. The simulation result is shown in figure 3.1, which is a three-dimensional ridge diagram summarizing the variation of relative real option value with changes in corn and soybean prices. The average relative real option value is 9.13%, with range from 0% to 26.30%. The typical pattern for the switching option value is that the option tends to

المنارة للاستشارات
www.manaraa.com

become more valuable as it gets closer to the money, i.e., the corn and soybean profits are similar to each other. These are the situations when there is significant uncertainty about planting intentions.

The simulation results presented in figure 3.1 are for the crop sequence of $\langle CS \rangle$. That is figure 3.1 represents the real option values when one year after soybeans and two years after corn. The real option values after the $\langle CC \rangle$ sequence is superimposed in figure 3.2, upon taking account for the estimated yield decline of 29.12 bu./ac. for corn after corn relative to corn after soybeans. Figure 3.2 indicates that compared with corn after soybeans, the same real option values are achieved at comparatively higher corn prices to offset the potential yield losses suffered by continuous corn.

Fixing the corn price as of 2007 at \$3.47/bu and soybeans price at \$8.76/bu, we simulate the effect of correlation changes on the real option value. The results are presented in table 3.4. In the base scenario, about 11% of the cash rent paid out by a tenant farmer is estimated to be the embedded real option including 0.24% input intensity option. The results of other cases indicate that the real option value decreases with an increase in the correlation between corn and soybean prices (ρ_8), as well as when the corn and nitrogen fertilizer correlation (ρ_9) increases, but increases with higher correlation between soybean and nitrogen fertilizer prices (ρ_{10}). The sensitivities are small and confirm our comparative statics results in the conceptual model.

Conclusion

After entering into a rental agreement in the fall, a tenant farmer has the flexibility to switch between corn and soybeans for the next crop year and to choose the input application level. The planting flexibility including switching and input application level can be treated as real option, which should be reflected in cash rent paid out to the landowner. Without taking into account the real option component, conventional NPV methods underestimate what farmers should pay for rental land. Applying contingent claims analysis, this study explicitly derives the value function of the real option. Comparative statics with respect to the volatilities of

المنارة للاستشارات
www.manaraa.com

underlying state variables and their correlations are derived and discussed.

After estimating and imposing the dependence structure between yields and input/output prices via a multivariate Gaussian copula, we simulate the switching and input intensity option value by Monte Carlo methods. The results show that, on average, cash rent valuation by the real option approach is about 13.5% higher than that measured by the traditional NPV method. The input intensity option is about 0.47%. The option value becomes higher as corn and soybean profits converge toward each other. Planting flexibility is worth little if profit from one crop looks as if it will dominate the others.

The approach we have taken may have other applications in land cash rent analysis. Recent fall and winter period grain prices have varied markedly, so that cash renters are increasingly concerned about experiencing high rents but low revenues. Some, such as Schnitkey and Lattz (2008) suggest that renting parties enter a price later contract whereby the rent is set several months after land control is agreed upon. This is an option. Implementing a price later rental contract would require a schedule mapping commodity and input prices into rents. Care in schedule-setting would include all the features brought out in our model.

Appendix

Real Option Valuation

This appendix considers the production decision of a tenant farmer facing input and output price uncertainty. Applying contingent claims analysis, we derive a closed-form solution for switching option valuation.

Production Decision

First, let's consider the production decision of a tenant farmer. We make the standard assumptions that markets are competitive and frictionless. There are perfectly competitive markets for corn, soybeans, and nitrogen fertilizer. Tenant farmers are price takers who can borrow and lend at the constant riskless rate r. Capital markets are assumed to be open all the time

المنارة للاستشارات
www.manaraa.com

so that a portfolio can be continuously rebalanced. Furthermore, we assume non-stochastic outputs for corn and soybeans in this section.

At planting time T_1, a tenant farmer is assumed to solve the following expected profit maximization problem when making the production and input choice decision:

$$\max\left\{\max_{y_C}\left[F_{T_1,C}y_C - K_C(y_C,W)\right], \max_{y_S}\left[F_{T_1,S}y_S - K_S(y_S,W)\right]\right\} \tag{A-1}$$

where y_i, $i \in \{C,S\}$ are the decision choice variables, denoting expected outputs of corn and soybeans, respectively. The $F_{T_1,i}$'s are expected output prices at harvest time T_2 as represented by planting time T_1 prices of futures contracts that mature at harvest time T_2. To promote concise notation, futures maturity date T_2 has been suppressed. We also simplify by ignoring futures basis in this section. The K_i's are the corn and soybean production cost functions. The input price vector is W.

For analytical convenience, we assume that the cost function for soybean production follows the output homogeneous and input price separable form:

$$K_S(y_S,W) = y_S^{\phi_S} k_S(W) \tag{A-2}$$

where $\phi_S > 1$ is the elasticity of scale parameter. The expected profit for soybean at planting time takes the form

$$\pi_S(F_{T_1,S},W) = \varphi_S F_{T_1,S}^{\delta_S} \tag{A-3}$$

where $\varphi_S = (1-\frac{1}{\phi_S})\left[\phi_S k_S(W)\right]^{-\frac{1}{\phi_S-1}}$ and $\delta_S = \frac{\phi_S}{\phi_S-1}$. By the property of profit function convexity, $\delta_S > 1$.[5]

For corn production, nitrogen fertilizer is the second most expensive input after farmland rent. Natural gas is the primary raw material in producing ammonia for nitrogen fertilizer. The volatile natural gas price largely affects nitrogen's price. For simplicity, we assume an actively traded futures or forward market for nitrogen fertilizer. We also assume that all

[5]Observe that inserting the time T_0 futures price into π_S, rather than the time T_1 price, will generally lead to an understatement of profit. This is due to an application of Jensen's inequality since π_S is convex in prices and $F_{T_1,S}$ is random from the viewpoint of T_0. So the traditional approach is likely to undervalue Ricardian rent for more than one reason.

المنارة للاستشارات
www.manaraa.com

nitrogen fertilizer is applied at planting.[6] A Cobb-Douglas cost function $K_C(y_C, W)$ is also assumed for corn production:

$$K_C(y_C, W) = y_C^{\phi_C} F_{T_1,N}^{\lambda} k_C(W) \tag{A-4}$$

where $\phi_C > 1$ is the elasticity of scale parameter, $F_{T_1,N}$ is the planting time price of an assumed nitrogen futures or forward contract that matures at planting time T_1, and $\lambda > 0$ is the demand elasticity of nitrogen fertilizer.[7] The planting time expected profit function for corn is[8]

$$\pi_C(F_{T_1,C}, F_{T_1,N}, W) = \varphi_C F_{T_1,C}^{\delta_C} F_{T_1,N}^{\delta_N} \tag{A-5}$$

where $\varphi_C = (1 - \frac{1}{\phi_C}) [\phi_C k_C(W)]^{-\frac{1}{\phi_C - 1}}$, $\delta_C = \frac{\phi_C}{\phi_C - 1}$, and $\delta_N = -\frac{\lambda}{\phi_C - 1}$. By the property of profit function convexity, $\delta_C > 1$.

These are the inputs that enter equations (3.1) and (3.2).

Valuation of the Crops

Given expected profit functions for crop production at planting time T_1, the crop present values at any time t before planting can be derived using the contingent claim analysis methods. Given a dynamically complete market for a contingent claim on the profits from the crop and using futures contract markets on the commodities, a tenant farmer may form a hedged portfolio to eliminate systemic risk and earn the risk-free rate of return instantaneously.

In the case of soybean, $F_{t,S}$ is considered to be the only stochastic state variable determining the value of soybean profit, $V_t^S(F_{t,S})$, at time t. By applying contingent claim analysis methods, it is shown that the value function $V_t^S(\cdot)$ is

$$V_t^S(F_{t,S}) = \varphi_S (F_{t,S})^{\delta_S} \exp\left\{ \left[\frac{1}{2} \sigma_{F_{t,S}}^2 \delta_S(\delta_S - 1) - r \right] (T_1 - t) \right\} \tag{A-6}$$

Demonstration of Equation (A-6):

[6] Studies indicate that in Iowa, application of nitrogen in fall potentially increases nitrogen loss and has a negative impact on profit. See www.ipm.iastate.edu/ipm/icm/2000/8-7-2000/falln.html for more information (last visited 10/13/2008).

[7] While corn requires nitrogen for adequate growth and grain production, soybean generally receives little or no nitrogen.

[8] Bear in mind that $F_{T_1,C}$ and $F_{T_1,S}$ are planting time T_1 prices of harvest time T_2 maturity contracts. The nitrogen contract used has planting maturity, and not harvest maturity, as planting maturity is what is needed for hedging.

المنارة للاستشارات
www.manaraa.com

By Itô's lemma, the value function $V_t^S(\cdot)$ follows the following stochastic process:

$$dV_t^S = \left(\frac{\partial V_t^S}{\partial F_{t,S}} \mu_{F_{t,S}} F_{t,S} + \frac{\partial V_t^S}{\partial t} + \frac{1}{2} \frac{\partial^2 V_t^S}{\partial F_{t,S}^2} \sigma_{F_{t,S}}^2 F_{t,S}^2 \right) dt + \frac{\partial V_t^S}{\partial F_{t,S}} \sigma_{F_{t,S}} F_{t,S} dz_S$$

It satisfies the Black differential equation (Hull 2002, p. 298):

$$\frac{\partial V_t^S}{\partial t} + \frac{1}{2} \frac{\partial^2 V_t^S}{\partial F_{t,S}^2} \sigma_{F_{t,S}}^2 F_{t,S}^2 = r V_t^S$$

with the only non-trivial boundary condition as $V_{T_1}^S(F_{T_1,S}) = \varphi_S F_{T_1,S}^{\delta_S}$. The unique value function $V_t^S(\cdot)$ satisfying the above partial differential equation and the boundary condition is given as equation (A-6). In addition, the value of soybeans profit follows an Itô process as

$$\frac{dV_t^S}{V_t^S} = \alpha_S dt + \sigma_{V_S} dz_{V_S}$$

where $\alpha_S = \delta_S \mu_{F_{t,S}} + r$ and $\sigma_{V_S} dz_{V_S} = \delta_S \sigma_{F_{t,S}} dz_S$. □

The expected corn and nitrogen fertilizer prices, $F_{t,C}$ and $F_{t,N}$, are considered to be the stochastic state variables driving the changes of corn value. Following Marcus and Modest (1984), it is shown that the value function $V_t^C(\cdot)$ is:

$$\begin{aligned} V_t^C(F_{t,C}, F_{t,N}) &= \varphi_C F_{t,C}^{\delta_C} F_{t,N}^{\delta_N} \exp\left\{ \left[\frac{1}{2} \delta_C (\delta_C - 1) \sigma_{F_{t,C}}^2 \right.\right. \\ &\quad \left.\left. + \frac{1}{2} \delta_N (\delta_N - 1) \sigma_{F_{t,N}}^2 + \delta_C \delta_N \sigma_{F_{t,C}} \sigma_{F_{t,N}} \rho_{CN} - r \right] (T_1 - t) \right\} \end{aligned} \quad \text{(A-7)}$$

Demonstration of Equation (A-7):

Applying Itô's lemma to the two state variables, $F_{t,C}$ and $F_{t,N}$, we get the dynamics of the corn value as:

$$\begin{aligned} dV_t^C &= \frac{\partial V_t^C}{\partial F_{t,C}} dF_{t,C} + \frac{\partial V_t^C}{\partial F_{t,N}} dF_{t,N} + \frac{\partial V_t^C}{\partial t} dt + \frac{1}{2} \frac{\partial^2 V_t^C}{\partial F_{t,C}^2} (dF_{t,C})^2 + \frac{1}{2} \frac{\partial^2 V_t^C}{\partial F_{t,N}^2} (dF_{t,N})^2 \\ &\quad + \frac{\partial^2 V_t^C}{\partial F_{t,C} \partial F_{t,N}} dF_{t,C} dF_{t,N} \\ &= \left(\frac{\partial V_t^C}{\partial F_{t,C}} \mu_{F_{t,C}} F_{t,C} + \frac{\partial V_t^C}{\partial F_{t,N}} \mu_{F_{t,N}} F_{t,N} + \frac{\partial V_t^C}{\partial t} + \frac{1}{2} \frac{\partial^2 V_t^C}{\partial F_{t,C}^2} \sigma_{F_{t,C}}^2 F_{t,C}^2 + \frac{1}{2} \frac{\partial^2 V_t^C}{\partial F_{t,N}^2} \sigma_{F_{t,N}}^2 F_{t,N}^2 + \right. \\ &\quad \left. \frac{\partial^2 V_t^C}{\partial F_{t,C} \partial F_{t,N}} F_{t,C} F_{t,N} \sigma_{F_{t,C}} \sigma_{F_{t,N}} \rho_{CN} \right) dt + \frac{\partial V_t^C}{\partial F_{t,C}} F_{t,C} \sigma_{F_{t,C}} dz_C + \frac{\partial V_t^C}{\partial F_{t,N}} F_{t,N} \sigma_{F_{t,N}} dz_N \end{aligned}$$

المنارة للاستشارات
www.manaraa.com

Following Marcus and Modest (1984), the hedging portfolio includes (1) the claim to the farmer's corn profit, (2) $\frac{\partial V_t^C}{\partial F_{t,C}}$ short positions in the corn futures contracts, (3) $\frac{\partial V_t^C}{\partial F_{t,N}}$ short positions in the assumed nitrogen fertilizer futures contracts, and (4) borrowing the amount of V_t^C at the risk free rate r. By design, the return on this portfolio is instantaneously riskless, which implies that the valuation function $V_t^C(\cdot)$ satisfies the partial differential equation

$$\frac{\partial V_t^C}{\partial t} + \frac{1}{2}\frac{\partial^2 V_t^C}{\partial F_{t,C}^2}\sigma_{F_{t,C}}^2 F_{t,C}^2 + \frac{1}{2}\frac{\partial^2 V_t^C}{\partial F_{t,N}^2}\sigma_{F_{t,N}}^2 F_{t,N}^2 + \frac{\partial^2 V_t^C}{\partial F_{t,C}\partial F_{t,N}} F_{t,C}F_{t,N}\sigma_{F_{t,C}}\sigma_{F_{t,N}}\rho_{CN} - rV_t^C = 0$$

with the boundary condition $V_{T_1}^C\left(F_{T_1,C}, F_{T_1,N}\right) = \varphi_C F_{T_1,C}^{\delta_C} F_{T_1,N}^{\delta_N}$. The value function satisfying the above partial differential equation and the boundary condition is as equation (A-7).

The value of corn profit follows a geometric Brownian motion as

$$\frac{dV_t^C}{V_t^C} = \alpha_C dt + \sigma_{V_C} dz_{V_C}$$

where $\alpha_C = \delta_C \mu_{F_{t,C}} + \delta_N \mu_{F_{t,N}} + r$, $\sigma_{V_C} dz_{V_C} = \delta_C \sigma_{F_{t,C}} dz_C + \delta_N \sigma_{F_{t,N}} dz_N$. □

Notice that

(a) the time t present value of crop V_t^i, $i \in \{C, S\}$ increases with higher expected output prices $F_{t,i}$ since $\frac{\partial V_t^i}{\partial F_{t,i}} = \frac{\delta_i V_t^i}{F_{t,i}} > 0$;

(b) the time t present value of corn V_t^C decreases with nitrogen fertilizer futures price $F_{t,N}$ for $\delta_N < 0$ since $\frac{\partial V_t^C}{\partial F_{t,N}} = \frac{\delta_N V_t^C}{F_{t,N}} < 0$;

(c) the time t value of the soybean crop goes up with an increase in the volatility of soybean's futures price $\sigma_{F_{t,S}}^2$, as implied by $\frac{\partial V_t^S}{\partial \sigma_{F_{t,S}}^2} = \frac{1}{2}\delta_S(\delta_S - 1)V_t^S(\cdot)(T_1 - t) > 0$;

(d) higher correlation between corn and nitrogen fertilizer prices ρ_{CN} reduces the value of corn for $\delta_C\delta_N < 0$ as $\frac{\partial V_t^C}{\partial \rho_{CN}} = \delta_C\delta_N\sigma_{F_{t,C}}\sigma_{F_{t,N}}V_t^C(\cdot)(T_1 - t) < 0$.

Value of the Switching Option

Demonstration of Equation (3.5):

We assume that the option value function $\Pi(\cdot)$ is linear homogeneous in V_t^C and V_t^S. Now let V_t^S be the numéraire with price of unity and define the price of V_t^C as $V_t = V_t^C/V_t^S$. Given (A-6) and (A-7), the relative value also follows geometric Brownian motion. Applying Itô's

المنارة للاستشارات
www.manaraa.com

lemma, the dynamics of V_t are given by

$$\frac{dV_t}{V_t} = \mu_V dt + \sigma_V dz_V$$

where $\mu_V = \alpha_C - \alpha_S + \delta_S^2 \sigma_{F_{t,S}}^2 - \delta_C \delta_S \sigma_{F_{t,C}} \sigma_{F_{t,S}} \rho_{CS} - \delta_S \delta_N \sigma_{F_{t,S}} \sigma_{F_{t,N}} \rho_{SN}$, and $\sigma_V dz_V = \delta_C \sigma_{F_{t,C}} dz_C + \delta_N \sigma_{F_{t,N}} dz_N - \delta_S \sigma_{F_{t,S}} dz_S$.

Now, the option to switch between corn and soybeans is a call option on the value of corn, with exercise price equal to unity and interest rate equal to zero. Applying the Black-Scholes formula on this special case, the value of the switching option is given as equation (3.5). □

Comparative Statics of the Switching Option

The option Vegas can be derived as follows

i. effect of a change in $\sigma_{F_{t,C}}$:

$$\begin{aligned} \frac{\partial \Pi}{\partial \sigma_{F_{t,C}}} &= V_t^C \Phi(d_1) \overbrace{\left[\delta_C(\delta_C - 1)\sigma_{F_{t,C}} + \delta_C \delta_N \sigma_{F_{t,N}} \rho_{CN}\right]}^{\text{A}} (T_1 - t) \\ &\quad + V_t^C \phi(d_1) \underbrace{\left(\delta_C^2 \sigma_{F_{t,C}} + \delta_C \delta_N \sigma_{F_{t,N}} \rho_{CN} - \delta_C \delta_S \sigma_{F_{t,S}} \rho_{CS}\right)}_{\text{B}} \frac{\sqrt{T_1 - t}}{\sigma_V} \end{aligned} \qquad \text{(A-8)}$$

where $\phi(\cdot)$ is the pdf of standard normal distribution. Note that if $\delta_C \approx 1$ and $\rho_{CN} \approx 0$, then term A in (A-8) is approximately 0. But term B could be negative if $\delta_C \sigma_{F_{t,C}} < \delta_S \sigma_{F_{t,S}} \rho_{CS}$, so that the whole expression can have negative value.

Demonstration of Equation (A-8):

$$\begin{aligned} \frac{\partial \Pi}{\partial \sigma_{F_{t,C}}} &= \frac{\partial V_t^C}{\partial \sigma_{F_{t,C}}} \Phi(d_1) + V_t^C \frac{\partial \Phi(d_1)}{\partial d_1} \frac{\partial d_1}{\partial \sigma_{F_{t,C}}} - \frac{\partial V_t^S}{\partial \sigma_{F_{t,C}}} \Phi(d_2) - V_t^S \frac{\partial \Phi(d_2)}{\partial d_2} \frac{\partial d_2}{\partial \sigma_{F_{t,C}}} \\ &= \frac{\partial V_t^C}{\partial \sigma_{F_{t,C}}} \Phi(d_1) + V_t^C \phi(d_1) \frac{\partial d_1}{\partial \sigma_{F_{t,C}}} - \frac{\partial V_t^S}{\partial \sigma_{F_{t,C}}} \Phi(d_2) - V_t^S \phi(d_2) \left(\frac{\partial d_1}{\partial \sigma_{F_{t,C}}} - \frac{\partial \sigma_V}{\partial \sigma_{F_{t,C}}} \sqrt{T_1 - t} \right) \\ &= \frac{\partial V_t^C}{\partial \sigma_{F_{t,C}}} \Phi(d_1) + V_t^S \phi(d_2) \frac{\partial \sigma_V}{\partial \sigma_{F_{t,C}}} \sqrt{T_1 - t} \end{aligned}$$

Equation (A-8) follows. The third equality holds because we have (a) $V_t^C \phi(d_1) = V_t^S \phi(d_2)$; (b) $\frac{\partial V_t^S}{\partial \sigma_{F_{t,C}}} = 0$. □

المنارة للاستشارات
www.manaraa.com

ii. effect of a change in $\sigma_{F_{t,S}}$:

$$\begin{aligned}\frac{\partial \Pi}{\partial \sigma_{F_{t,S}}} &= V_t^S \Phi(d_2) \overbrace{\left[\delta_S(\delta_S - 1)\sigma_{F_{t,S}}\right]}^{\mathrm{A}'} (T_1 - t) \\ &\quad + V_t^S \phi(d_2) \underbrace{\left(\delta_S^2 \sigma_{F_{t,S}} - \delta_S \delta_N \sigma_{F_{t,N}} \rho_{SN} - \delta_S \delta_C \sigma_{F_{t,S}} \rho_{CS}\right)}_{\mathrm{B}'} \frac{\sqrt{T_1 - t}}{\sigma_V}\end{aligned}$$

A sufficient condition for a positive overall effect is $\delta_S \sigma_{F_{t,S}} > \delta_N \sigma_{F_{t,N}} \rho_{SN} + \delta_C \sigma_{F_{t,S}} \rho_{CS}$ given that $\delta_S > 1$. If $\delta_S \approx 1$, then $\mathrm{A}' \approx 0$, but B' could be negative. So a negative overall effect cannot be precluded.

iii. effect of a change in $\sigma_{F_{t,N}}$:

$$\begin{aligned}\frac{\partial \Pi}{\partial \sigma_{F_{t,N}}} &= V_t^C \Phi(d_1) \overbrace{\left[\delta_N(\delta_N - 1)\sigma_{F_{t,N}} + \delta_C \delta_N \sigma_{F_{t,C}} \rho_{CN}\right]}^{\mathrm{A}''} (T_1 - t) \\ &\quad + V_t^C \phi(d_1) \underbrace{\left(\delta_N^2 \sigma_{F_{t,N}} - \delta_C \delta_N \sigma_{F_{t,C}} \rho_{CN} - \delta_S \delta_N \sigma_{F_{t,S}} \rho_{SN}\right)}_{\mathrm{B}''} \frac{\sqrt{T_1 - t}}{\sigma_V}\end{aligned}$$

Also note that if $\delta_N \approx 1$ and $\rho_{CN} \approx 0$, then $\mathrm{A}'' \approx 0$, but B'' could be negative if $\sigma_{F_{t,N}} < \sigma_{F_{t,S}} \rho_{SN}$.

In addition, the partial derivative of the switching option with respect to correlation between underlying price variables can be derived as:

iv. effect of a change in ρ_{CS}:

$$\frac{\partial \Pi}{\partial \rho_{CS}} = -V_t^C \phi(d_1) \delta_C \delta_S \sigma_{F_{t,C}} \sigma_{F_{t,S}} \frac{\sqrt{T_1 - t}}{\sigma_V} < 0 \tag{A-9}$$

Demonstration of Equation (A-9):

$$\begin{aligned}\frac{\partial \Pi}{\partial \rho_{CS}} &= \frac{\partial V_t^C}{\partial \rho_{CS}} \Phi(d_1) + V_t^C \phi(d_1) \frac{\partial d_1}{\partial \rho_{CS}} - \frac{\partial V_t^S}{\partial \rho_{CS}} \Phi(d_2) - V_t^S \phi(d_2) \frac{\partial d_2}{\partial \rho_{CS}} \\ &= -V_t^C \phi(d_1) \frac{\partial \sigma_V}{\partial \rho_{CS}} \sqrt{T_1 - t}\end{aligned}$$

Equation (A-9) follows. The second equality holds because we have (a) $V_t^C \phi(d_1) = V_t^S \phi(d_2)$; (b) $\frac{\partial V_t^C}{\partial \rho_{CS}} = \frac{\partial V_t^S}{\partial \rho_{CS}} = 0$. □

v. effect of a change in ρ_{CN}:

$$\frac{\partial \Pi}{\partial \rho_{CN}} = V_t^C \delta_C \delta_N \sigma_{F_{t,C}} \sigma_{F_{t,N}} \left[\Phi(d_1)(T_1 - t) + \phi(d_1)\sqrt{T_1 - t}/\sigma_V\right] < 0 \quad \text{as} \quad \delta_C > 0 > \delta_N.$$

المنارة للاستشارات
www.manaraa.com

vi. effect of a change in ρ_{SN}:

$$\frac{\partial \Pi}{\partial \rho_{SN}} = -V_t^C \phi(d_1)\delta_S \delta_N \sigma_{F_{t,S}} \sigma_{F_{t,N}} \sqrt{T_1 - t}/\sigma_V > 0 \quad \text{as} \quad \delta_S > 0 > \delta_N.$$

References

Black, F., and M. Scholes. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81:637-654.

Calkins, P., and D. DiPietre. 1983. *Farm Business Management: Successful Decisions in a Changing Environment*. New York: Macmillan Publishing.

Cherubini U., E. Luciano, and W. Vecchiato. 2004. *Copula Methods in Finance*. New York: John Wiley & Sons.

Dhuyvetter, K., and T. Kastens. 2002. Landowner vs. Tenant: Why Are Land Rents So High? Paper presented at the Risk and Profitability Conference, Manhattan KS, 15-16 August.

Dixit, A., and R. Pindyck. 1994. *Investment Under Uncertainty*. Princeton, New Jersey: Princeton University Press.

Du, X., D.A. Hennessy, and W.M. Edwards. 2007. Determinants of Iowa Cropland Cash Rental Rates: Testing Ricardian Rent Theory. CARD Working Paper 07-WP 454, Center for Agricultural and Rural Development, Iowa State University.

Duffy, M., and D. Smith. 1979-2008. Estimated Costs of Crop Production in Iowa. Iowa State University Extension Publication FM-1712.

Edwards, W.M., and D. Smith. 2008. Cash Rental Rates for Iowa 2008 Survey. Iowa State University Extension Publication FM1851.

Goodwin, B.K., A.K. Mishra, and F. Ortalo-Magné. 2004. Landowners' Riches: The Distribution of Agricultural Subsidies. Working Paper, School of Business, University of Wisconsin, Madison.

Hennessy, D.A. 2006. On Monoculture and The Structure of Crop Rotations. *American Journal of Agricultural Economics* 88:900-914.

Hull, J. 2002. *Options, Futures, and Other Derivatives* (5th Ed.). Upper Saddle River, NJ: Prentice Hall.

Joe, H. 1997. *Multivariate Models and Dependence Concepts*. London: Chapman & Hall.

–. 2005. Asymptotic Efficiency of the Two-stage Estimation Method for Copula-based Models. *Journal of Multivariate Analysis* 94:401-419.

المنارة للاستشارات
www.manaraa.com

Just, R., and Q. Weninger. 1999. Are Crop Yields Normally Distributed? *American Journal of Agricultural Economics* 81:287-304.

Kay, R.D., W.M. Edwards, and P. Duffy. 2004. *Farm Management*. Boston: McGraw-Hill.

Ker, A., and K. Coble. 2003. Modeling Conditional Yield Densities. *American Journal of Agricultural Economics* 85:291-304.

Ker, A., and B.K. Goodwin. 2000. Nonparametric Estimation of Crop Insurance Rates Revisited. *American Journal of Agricultural Economics* 83:463-478.

Kurkalova, L.A., C. Burkart, and S. Secchi. 2004. Cropland Cash Rental Rates in the Upper Mississippi River Basin. Technical Report, Center for Agricultural and Rural Development, Iowa State University.

Lence, S., and A. Mishra. 2003. The Impacts of Different Farm Programs on Cash Rents. *American Journal of Agricultural Economics* 85:753-761.

Luong, Q., and L. Tauer. 2006. A Real Options Analysis of Coffee Planting in Vietnam. *Agricultural Economics* 35:49-57.

Mallarino, A., E. Ortiz-Torres, and K. Pecinovsky. 2004. Effects of Crop Rotation and Nitrogen Fertilization on Crop Production. Iowa State University Agronomy Extension Annual Report.

Marcus, A., and D. Modest. 1984. Futures Markets and Production Decisions. *Journal of Political Economy* 92:409-426.

–. 1986. The Valuation of a Random Number of Put Options: An Application to Agricultural Price Supports. *Journal of Financial and Quantitative Analysis* 21:73-86.

Margrabe, W. 1978. The Value of an Option to Exchange One Asset for Another. *Journal of Finance* 33:177-186.

Merton, R. 1973. Theory of Rational Option Pricing. *The Bell Journal of Economics and Management Science* 4:141-183.

–. 1977. On the Pricing of Contingent Claims and The Modigliani-Miller Theorem. *Journal of Financial Economics* 5:241-249.

Mußhoff, O., and N. Hirschauer. 2008. Investment Planning Under Uncertainty and Flexibility: The Case of a Purchasable Sales Contract. *The Australian Journal of Agricultural and Resource Economics* 52:17-36.

Nelsen R.B. 1999. *An Introduction to Copulas*. New York: Springer-Verlag.

Nelson, C., and P. Preckel. 1989. The Conditional Beta Distribution as a Stochastic Production Function. *American Journal of Agricultural Economics* 71:370-78.

المنارة للاستشارات
www.manaraa.com

Odening, M., O. Mußhoff, and A. Balmann. 2005. Investment Decisions in Hog Finishing: An Application of The Real Options Approach. *Agricultural Economics* 32:47-60.

Oi, W. 1961. The Desirability of Price Instability Under Perfect Competition. *Econometrica* 29:58-64.

Olson, K. 2004. *Farm Management: Principles and Strategies.* Ames, IA: Blackwell Publishing.

Schnitkey G., and D. Latta. 2008. 2009 Rental Decision Given Volatile Commodity Prices and Higher Input Costs. Illinois Farm Economics Update. October 15.

Sklar, A. 1959. Fonctions de répartition à n dimensions et leurs marges. *Pub. Inst.Statist. Univ. Paris* 8:229-231.

Tejeda, H.A., and B.K. Goodwin. 2008. Modeling Crop Prices through a Burr Distribution and Analysis of Correlation between Crop Prices and Yields using a Copula Method. Paper presented at AAEA annual meeting, Orlando FL, 27-29 July.

Tzouramani, L., and K. Mattas. 2004. Employing Real Options methodology in Agricultural Investments: The Case of Greenhouse Construction. *Applied Economics Letter* 11:355-359.

Vedenov, D. 2008. Application of Copulas to Estimation of Joint Crop Yield Distributions. Paper presented at AAEA annual meeting, Orlando FL, 27-29 July.

Yan, J. 2008. Enjoy the Joy of Copulas: With a Package copula. *Journal of Statistical Software* 21:1-21.

Zhu, Y., S.K. Ghosh, and B.K. Goodwin. 2008. Modeling Dependent in the Design of Whole Farm Insurance Contract - a Copula-Based Model Approach. Paper presented at AAEA annual meeting, Orlando FL, 27-29 July.

المنارة للاستشارات

www.manaraa.com

Table 3.1 OLS Regression Results for Corn and Soybean Yields

	Estimates	Std. Error	t Value	$P(> \|t\|)$
Corn Yield				
Year	0.27	0.089	3.02	0.0026
Nitrogen	0.68	0.025	27.26	< 0.001
$(\text{Nitrogen})^2$	-0.00163	0.000099	-16.37	< 0.001
Dummy for CC	-29.12	1.29	-22.65	< 0.001
Intercept	87.69	1.843	47.59	< 0.001
R^2	0.5371			
Soybean Yield				
Year	0.79	0.092	8.67	< 0.001
Dummy for CCS	4.67	1.40	3.33	0.001
Intercept	34.27	1.65	20.74	< 0.001
R^2	0.2797			

المنارة للاستشارات
www.manaraa.com

Table 3.2 Estimates of Marginal Distributions and the Gaussian Copula

Marginal Distributions		Parameter 1	Parameter 2
Corn yield	Beta	7.04	2.81
Soybean yield	Beta	6.02	2.55
Corn price	Normal	0.0011	0.11
Soybean price	Normal	0.0018	0.096
Nitrogen price	Normal	0.012	0.063
Dependent parameter	Estimate	z-value	p> $\|z\|$
Corn yield			
$\sim$ soybean yield (ρ_1)	0.6689	7.29	< 0.001
$\sim$ corn price (ρ_2)	-0.4252	-2.84	0.0045
$\sim$ soybean price (ρ_3)	-0.2352	-1.34	0.18
$\sim$ nitrogen price (ρ_4)	-0.2111	-1.14	0.25
Soybean yield			
$\sim$ corn price (ρ_5)	-0.3589	-2.25	0.024
$\sim$ soybean price (ρ_6)	-0.1446	-0.79	0.43
$\sim$ nitrogen price (ρ_7)	-0.2683	-1.49	0.13
Corn price			
$\sim$ soybean price (ρ_8)	0.7645	11.64	< 0.001
$\sim$ nitrogen price (ρ_9)	0.1693	0.89	0.37
Soybean price			
$\sim$ nitrogen price (ρ_{10})	0.0496	0.25	0.80

المنارة للاستشارات
www.manaraa.com

Table 3.3 Simulation Results for Real Option Value, 1995-2008

Year	Cash Prices			Production Cost		Profit				Option Value			
	Corn	Soybeans	Nitrogen	Corn	Soybeans	Corn Profit $\hat{V}_3$	Corn Profit $\hat{V}_4$	Soybean Profit	% of Draws Corn is Grown	Traditional Rent	Real Option Rent	% Real Option Value	% Input Intensity Option
1995	2.9327	6.0655	0.2	86.48	75.33	205.93	205.55	219.28	45.30	219.28	262.93	19.90	0.19
1996	2.4061	6.6889	0.21	94.60	83.95	368.99	368.53	276.58	67.60	368.99	403.46	9.34	0.13
1997	2.4573	6.4437	0.22	97.34	86.3	276.69	276.09	321.15	38.00	321.15	367.85	14.54	0.22
1998	1.8537	5.0178	0.19	100.93	91.99	282.14	281.48	307.37	42.24	307.37	362.60	17.97	0.23
1999	1.632	4.297	0.16	101.76	90.39	183.83	183.19	225.94	35.60	225.94	259.11	14.68	0.35
2000	1.778	4.3262	0.16	101.65	89.44	151.32	150.79	182.98	36.40	182.98	213.37	16.61	0.34
2001	1.7339	4.0124	0.21	101.01	88.95	174.45	173.97	190.72	41.96	190.72	230.79	21.01	0.28
2002	2.1355	5.11	0.21	99.95	86.57	164.58	163.73	177.95	42.24	177.95	217.35	22.14	0.51
2003	2.0923	7.01	0.20	101.10	87.14	229.65	228.95	251.11	42.18	251.11	299.12	19.12	0.30
2004	1.6247	4.9195	0.25	105.74	92.63	223.62	222.98	382.29	17.00	382.29	399.08	4.39	0.29
2005	1.4609	5.0962	0.30	120.03	96.53	118.06	116.77	236.83	16.14	236.83	249.39	5.30	1.10
2006	3.2196	5.3006	0.35	134.26	106.79	69.53	67.44	246.69	7.30	246.69	254.13	3.10	2.08
2007	3.4696	8.7626	0.31	147.48	107.58	352.31	351.04	262.66	63.00	352.31	392.27	11.34	0.36
2008	–	–	0.46	175.15	124.16	369.66	368.74	492.82	29.06	492.82	543.02	10.18	0.25

Note: Corn profit: $\hat{V}_3 = \frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,C,N^*})$, $\hat{V}_4 = \frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,C,N})$; soybean profit: $\frac{1}{n}\sum_{i=1}^{n}(\pi^i_{T_1,S})$; % of draws corn is grown: $\%\left(\pi^i_{T_1,C} > \pi^i_{T_1,S}\right)$; traditional rent: $\hat{V}_1(t)$; real option rent: $\hat{V}_2(t)$; % real option value: $\widehat{\%\Pi_1} = \left(\frac{\hat{V}_2(t)}{\hat{V}_1(t)} - 1\right) \times 100\%$; % input intensity option: $\widehat{\%\Pi_2} = \left(\frac{\hat{V}_3(t)}{\hat{V}_4(t)} - 1\right) \times 100\%$.

المنارة للاستشارات
www.manaraa.com

Table 3.4 Simulation Results for Changing Correlations, 2008

Scenario	Corn Profit $\hat{V}_3$	Corn Profit $\hat{V}_4$	Soybean Profit	% of Draws of Corn	Traditional Rent	Real Option Rent	% Real Option	% Input Intensity
Base case	374.77	373.88	493.68	28.90	493.68	546.35	10.67	0.24
$\rho_1 \uparrow 0.1$	372.99	372.08	496.78	28.00	496.78	545.66	9.84	0.24
$\rho_2 \uparrow -0.1$	368.52	367.66	497.19	27.70	497.19	539.73	8.56	0.23
$\rho_3 \uparrow -0.1$	376.10	375.12	503.09	29.86	503.09	562.28	11.76	0.26
$\rho_4 \uparrow -0.1$	376.55	375.62	496.35	29.08	496.35	549.65	10.74	0.25
$\rho_5 \uparrow -0.1$	370.64	369.74	488.47	30.44	488.47	548.60	12.31	0.24
$\rho_6 \uparrow -0.1$	375.18	374.29	487.64	29.28	487.64	538.20	10.37	0.24
$\rho_7 \uparrow -0.1$	373.63	372.69	495.19	28.94	495.19	545.95	10.25	0.25
$\rho_8 \uparrow 0.1$	378.80	377.87	500.45	25.16	500.45	538.85	7.67	0.24
$\rho_9 \uparrow 0.1$	379.50	378.67	499.34	28.46	499.35	550.65	10.28	0.22
$\rho_{10} \uparrow 0.1$	374.55	373.62	495.78	28.32	495.78	549.68	10.87	0.25

Note: For $\rho_2 - \rho_7$, which denote negative correlations, $\uparrow -0.1$ means increasing the absolute value of the correlation by 0.1.

المنارة للاستشارات
www.manaraa.com

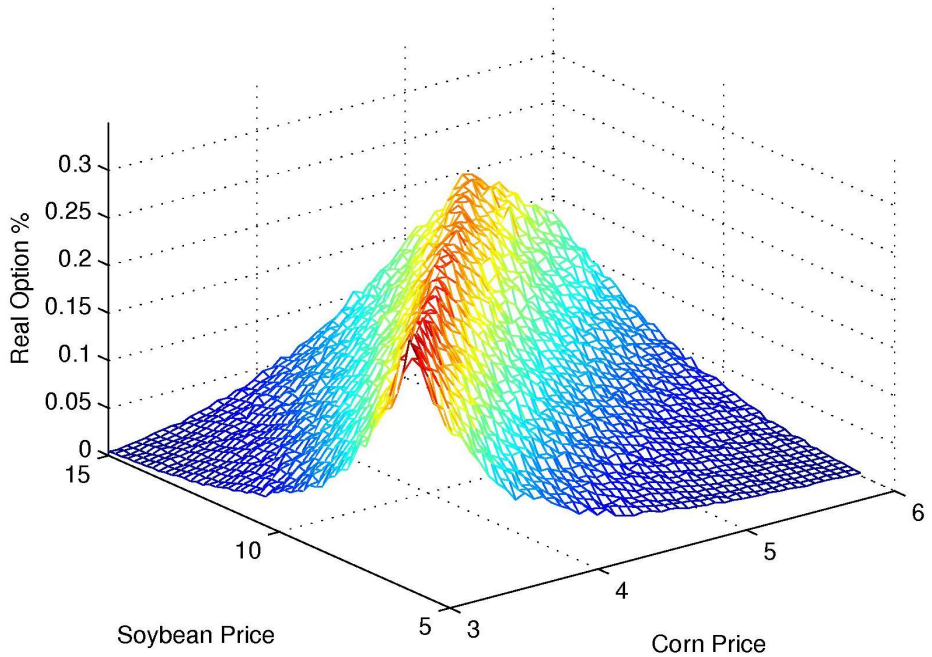


Figure 3.1 Simulated Real Option Value under Corn-Soybean Rotation, 2007

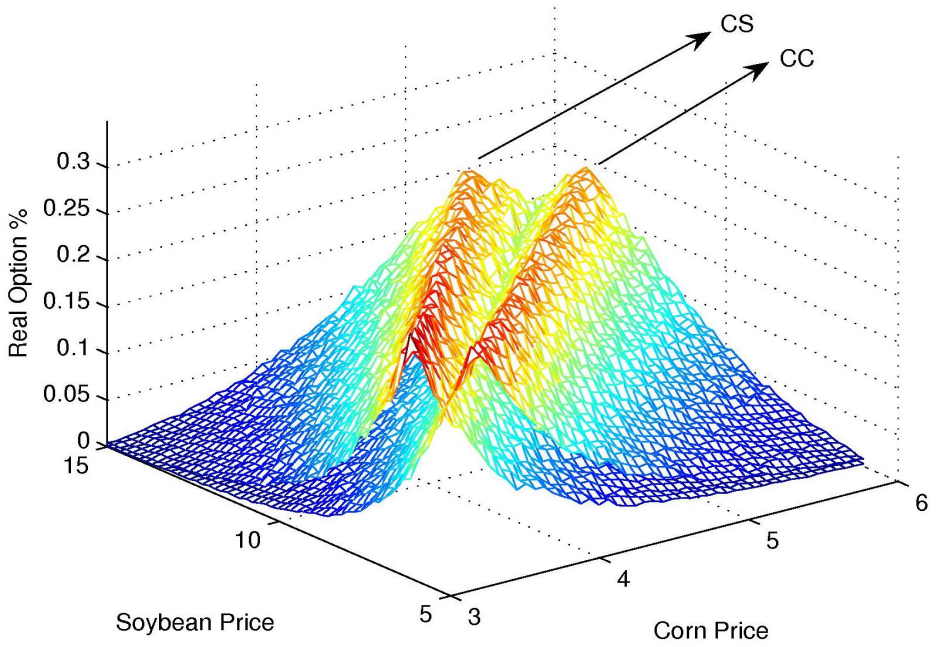


Figure 3.2 Real Option Value under Corn-Corn and Corn-Soybean Rotations, 2007

المنارة للاستشارات
www.manaraa.com

4. THE IMPACT OF ETHANOL PRODUCTION ON U.S. AND REGIONAL GASOLINE PRICES AND ON WELFARE

Abstract

We quantify the impact of ethanol production on wholesale gasoline price employing pooled regional time-series data from January 1995 to March 2008. This analysis suggests that the growth in ethanol production has caused wholesale gasoline prices to be 14¢/gallon lower than would otherwise have been the case. Furthermore, the negative impact of ethanol on retail gasoline price is found to vary considerably across regions. The Midwest region has the biggest impact at 34¢/gallon, while the Rocky Mountain region had the smallest impact, 7¢/gallon. The results indicate that the reduction in gasoline price comes at the expense of refiners' profits and structure changes in the refining industry significantly impact gasoline prices. This study estimates the welfare changes for consumers and producers resulting from ethanol production and related support polices in 2007. The welfare estimates are based on a transparent analytical model of multiple markets including corn, ethanol, gasoline, and transportation fuel. The results suggest a net welfare loss of $0.28 billion from the support policies. We validate the model's underlying assumption and test for the results' sensitivity to assumed parameters.

Key words: consumer surplus, crack ratio, crack spread, deadweight loss, subsidy, substitution.

المنارة للاستشارات

www.manaraa.com

Introduction

World oil consumption is projected to grow by 1 million barrels per day in 2008 (Energy Information Administration, EIA hereafter, 2008). Rising consumption comes mainly from continued economic growth in developing countries especially China and India. Declining production in countries outside of the Organization of the Petroleum Exporting Countries (OPEC), together with weak OPEC supply, is in part responsible for the recent reduction in global oil supplies. Biofuels are becoming a major source of incremental fuel supply and make up a significant portion of the growth in fuel production (Blanch et al. 2008). The non-OPEC supply growth forecast for 2008 by the International Energy Agency (IEA) is 455,000 barrel per day, of which 72% will be in the form of biofuels.

The U.S. consumed approximately 146 billion gallons of petroleum in 2007. Responding to increased mandates and oil prices, fuel ethanol production in the United States increased from 1.63 billion gallons in 2000 to 6.5 billion gallons in 2007 (RFA 2008), which is approximately 81.8 million barrels of oil equivalent (BP 2008). In July 2008, production had reached 9.3 billion gallons on an annualized basis, and ethanol plants with an additional 4.3 billion gallons of capacity were under construction.

Ethanol is blended with gasoline to improve octane and performance in about 50% of the nation's gasoline supply. Typically, a gallon of ethanol blend will have 10% ethanol and 90% gasoline. This gallon of ethanol blend will contain approximately 96.81% of the energy of a gallon of gasoline (Tokgoz et al. 2007) and will use approximately one-tenth as much fuel energy to produce as it contains (Wang et al. 2007). Therefore, ethanol has essentially added to U.S. gasoline supplies by utilizing solar energy to grow the crop, coupled with energy from natural gas and coal to manufacture the farm equipment and fertilizer used in crop production. According to estimates by the U.S. Department of Agriculture (USDA) and Department of Energy (DOE), ethanol production in 2008 will have reduced gasoline demand by approximately 5%, or 7.2 billion gallons (USDA/DOE 2008).

One purpose of this paper is to estimate the impact of the increase in ethanol supply on the U.S. gasoline market. For this purpose, we need to separate the impact of ethanol from

المنارة للاستشارات
www.manaraa.com

the other forces driving gasoline prices. We examine the crack ratio, the price of gasoline relative to the price of crude oil, and the crack spread, an accepted proxy for the profitability of the refining industry and we control for other factors that might influence these ratios. The estimates of the impact on gasoline prices are calculated for the U.S. as a whole and for each of five regions within the U.S. The motivation for conducting the regional analysis is that if ethanol is affecting gasoline prices, then we hypothesize that this impact will be largest in the Midwest where regional ethanol production and utilization is at its maximum.

The ethanol industry in the U.S. receives support on several different fronts. There are three major categories: (1) Budgetary support measures, including a 51¢-per-gallon tax credit to refiners blending ethanol with gasoline. This is scheduled to fall to 45¢ in January 2009. (2) A renewable fuel standard (RFS) that requires U.S. fuel producers to blend into gasoline at least certain amount of renewable fuel, ranging from 9 billion gallons in 2008 to 36 billion gallons by 2022. (3) Trade restrictions, including a 2.5% ad valorem tariff and a per unit tariff of 54¢ per gallon. The benefits and pitfalls of this level of government support have been at the center of recent debate.

In this study, based on the estimated substitution effect of ethanol on gasoline, we investigate the distribution of welfare gains and losses from the ethanol blenders tax credit among producers and consumers in the corn, ethanol, gasoline and fuel markets and estimate the overall welfare impact of the U.S. ethanol subsidy. To the best of our knowledge, our study is the first to include the impact of ethanol on the gasoline market, and to acknowledge in a multi-market framework that prior to the existence of a large ethanol industry, commodity markets were already in a second best situation.

Our contribution is three-fold. First, estimation results show that over the sample period, ethanol production had a significant negative effect of 14¢ per gallon on wholesale gasoline prices. Results for individual regions indicate that the largest impact of ethanol on gasoline is found in the Midwest region where regular retail gasoline prices were reduced by 34¢ per gallon. The West Coast and East Coast are found to have experienced 25¢ and 23¢ reduction in the retail gasoline price, while for the Gulf Coast region the average price drop is about

المنارة للاستشارات
www.manaraa.com

20¢. The smallest impact is found in the Rocky Mountain region, at 7¢ per gallon, possibly because of its comparatively low ethanol consumption. We also quantify the impact of ethanol production on refinery profitability represented by 3-2-1 crack spread. The results suggest that the reduction in gasoline prices came at the expense of refiners' profits, which is about $1.33 per barrel.

Our second contribution is to examine the effects of important structure changes in the petroleum refining industry: (1) changes in refinery ownership related to mergers and acquisitions, and (2) increasing refinery complexity and downstream processing capacity. The results indicate that refinery market concentration and refinery complexity lead to higher gasoline prices and refinery profits. Our third contribution is that we develop an analytical model explicit in its accounting of ethanol, gasoline, and fuel markets. We estimate the welfare impacts on agricultural and energy markets, and on overall welfare change after accounting for reduced loan deficiency payments. The welfare estimates are done by both traditional consumer (producer) surplus formulas and the compensating variation measure.

The paper proceeds by providing a review of previous work regarding the determining factors of gasoline price and the welfare analysis of ethanol supporting policies. The following section presents an empirical analysis of the impact of ethanol production on gasoline price. It starts with a brief introduction of the petroleum refining process and the U.S. regional refinery markets. A detailed description of, and motivation for, each of the explanatory variables used in the analysis follows. The estimation method and results for a fixed effects model are presented. In the welfare analysis section, we discuss an analytical model and empirical estimates of welfare changes. We validate the model's underlying assumption and test for the results' sensitivity to assumed parameters. The paper concludes with a summary of the major findings and provides suggestions for future research.

Previous Work

Analysis of the effect of ethanol on gasoline prices and on refinery profitability has been largely neglected in the literature. Eidman (2005) points out that ethanol has a strong positive cor-

المنارة للاستشارات
www.manaraa.com

relation with gasoline prices. Employing an international ethanol model, Tokgoz and Elobeid (2007) analyze the price linkage between ethanol and gasoline markets. Vedenov et al. (2006) suggests that blending ethanol into gasoline would generate lower gasoline price volatility and that switching from conventional gasoline to an ethanol blend is an economically sound decision. There are a considerable number of government and academic studies that seek to explain gasoline price changes and adjustments in the wholesale market and to identify factors that contribute to gasoline price spikes.[1]

A recurring theme in the literature is the contribution of market concentration on the price of gasoline. Oladunjoye (2008) finds that market concentration has a significant asymmetric effect on the response of gasoline prices to crude price shocks. The U.S. Government Accounting Office (GAO 2004) concludes that increased market concentration generally led to higher wholesale gasoline prices from the mid-1990s through 2000. Examining wholesale price responses in 188 gasoline markets in the U.S., Borenstein and Shepard (2002) find that refinery firms with market power generally adjust prices more slowly than do competitive firms. Geweke (2003) provides a comprehensive survey on this subject.

A related line of research separates the effects of regional gasoline content regulations on gasoline price spikes. Muehlegger (2006) estimates that price increases due to content regulations through increased production costs and fuel incompatibility are 9.3¢, 9.6¢, and 10.0¢ per gallon in California, Illinois, and Wisconsin, respectively. Brown et al. (2008) find that content regulations are associated with an increase in wholesale and retail gasoline prices of 3¢6¢ per gallon. Various studies support asymmetric price adjustments on the U.S. wholesale gasoline market (e.g., Radchenko 2005a,b; Kaufmann and Laskowshi 2005; Borenstein et al. 1997), while Bachmeier and Griffin (2003) find no evidence of asymmetry in wholesale gasoline prices.

Another strand of literature investigates various issues related to the petroleum refining industry. The important examples include the following studies. Griffin (1972) and Adams

[1] A number of government studies qualitatively analyze gasoline price spikes and the effect of market concentration on gasoline prices, including, for example, Pirog (2005) and EIA (1996). We don't include these studies in this review.

المنارة للاستشارات
www.manaraa.com

and Griffin (1972) provide a linear programming application of process analysis to petroleum refining. Using a multiproduct restricted cost function with adjustment costs, Considine (1992) analyzes the short-run petroleum product supply in the U.S. Considine (1997) analyzes the determinants of inventory investment under joint production for the petroleum refining industry. Asano (2002) employs five econometric models to examine lumpy investment and investigate the investment behavior of the U.S. petroleum refining industry. Chen (2002) investigates the survival of U.S. petroleum refining plants for the period 1981-86 and examines the duration dependence and determinants of a plant's lifetime.

There are an increasing number of studies on the welfare analysis of ethanol subsidies. Babcock (2008) simulates the welfare impacts of various government ethanol policies in a model of multiple integrated markets. He finds that U.S. ethanol policy induces large welfare transfer from taxpayers and non-ethanol corn users to corn producers, fuel blenders, and ethanol producers, as well as large associated net welfare loss. Gardner (2007) used a vertical market model of corn, ethanol, and byproducts and compares welfare effects of the government's subsidy on corn through deficiency payments and the government subsidy on ethanol produced from corn. He finds that the net deadweight loss of the corn and ethanol subsidies is likely to be in the billions of dollars annually. The deadweight loss of ethanol subsidy is much higher than that of deficiency payment. This conclusion is based on the assumption that corn price increases by only 4¢ resulting from the ethanol subsidy, which is much smaller than what happened in the recent corn market. Schmitz, Moss, and Schmitz (2007) calculate the impact of ethanol subsidies on corn used for ethanol and indicate that treasury cost of the ethanol tax credit is about $1.0 billion lower than direct payment to corn farmers.

Martinez-Gonzalez, Sheldon, and Thompson (2007) use a partial equilibrium trade model and back-of the envelope formula to calculate welfare effects of distortions in the ethanol market. Elobeid and Tokgoz (2008) analyze the impact of trade liberalization and removal of the federal tax credit in U.S. on ethanol markets but excluding energy markets in a multi-market international ethanol framework. They find that trade liberalization induces welfare loss of ethanol and corn producers and a gain in consumer surplus of ethanol through lower

المنارة للاستشارات
www.manaraa.com

ethanol and corn prices. Also, the removal of the tariff and tax credit result in declines in corn farmers, ethanol producers, and ethanol consumer surpluses. de Gorter and Just (2007) analyze the efficiency and income distribution effects of the ethanol tax credit and illustrate the potential welfare effects empirically, they find a net deadweight loss is $1.07 billion per year. Taheripour and Tyner (2007) find that the share of ethanol subsidy received by ethanol producers (1) increases with the elasticity of substitution between ethanol and gasoline and also the proportion of ethanol blended in fuel; (2) decreases with the price elasticity of ethanol. They concluded that ethanol industry is, and will continue to be in a good position to capture the ethanol tax credit regardless of its current share.

Empirical Analysis

This section starts with a brief introduction of petroleum refining process and regional refinery markets. Employing a fixed effects panel data model that takes serial autocorrelation and heteroskedasticity into account, we empirically estimation the impact of ethanol production on gasoline price after controlling other determining factors.

Background

A typical petroleum refinery is a complex chemical processing and manufacturing plant, with crude oil feedstocks going in, and refined products coming out. In the first phase of petroleum processing, refineries heat and separate crude oil into certain intermediate products using an atmospheric distillation unit. "Downstream" from this initial refinery process are more complex processing units that are used to increase a refinery's flexibility to process a wide range of crude oils and increase the yield of lighter petroleum products such as gasoline.

Separation products from the distillation unit are upgraded by changing their chemical structure through processes such as coking, hydrocracking, and fluid catalytic cracking. After removing impurities, the refiner blends various products into end products. End products are classified into light products, including gasoline, jet fuel, kerosene and diesel fuel, and heavier products such as fuel oil and coke. The mix of refined products can be adjusted to a limited

المنارة للاستشارات
www.manaraa.com

extent in response to relative prices of the final products under the constraints of production capacity, availability of crude oil, and adjustment costs.

Crude oil is a heterogeneous good whose density is commonly measured by API (American Petroleum Institute) gravity. The higher the API number, the lighter the crude. West Texas Intermediate (WTI) crude oil is classified as a light sour crude oil, having a typical API gravity of about 33 degrees and a sulfur content of about 1.6%. The price difference between light and heavy crude oils and light and heavy refinery products provides a strong incentive for installing downstream processing facilities in a refinery. Over the past 20 years, the refining industry shifted investment from crude oil distillation capacity to downstream processing capacity (EIA 2007).

There are three main octane-level-based grades of finished gasoline: regular, mid-grade, and premium. Finished gasoline is delivered from oil refineries by barge or pipeline to regional wholesale terminals. Then, gasoline is sold to retail stations either at a bulk price, a rack price, or the Dealer Tank Wagon (DTW) price.

We use the PADDs to define refinery product markets, and use these PADD districts interchangeably with more intuitive regional names. The five regions are the East Coast (PADD I), the Midwest (PADD II), the Gulf Coast (PADD III), the Rocky Mountains (PADD IV), and the West Coast (PADD V). These five geographically distinct regions are also very different in terms of their economic conditions, oil and petroleum characteristics, oil-related pipeline infrastructure, and local product supply and demand conditions.

The East Coast region (PADD I) has the highest demand for refined products but has a very limited refinery capacity. Its regional demand is largely satisfied by the Gulf Coast and by foreign imports. The Midwest region (PADD II) leads the nation in ethanol production, mainly because of its leading role in production of corn, which is the primary feedstock for ethanol production. Much of the crude oil used in the Midwest is piped in from the Gulf Coast and Canada.

The Gulf Coast region (PADD III) produces over 50% of the nation's crude oil and 47% of its final refined products. This region also serves as a national hub for crude oil and is the center

المنارة للاستشارات
www.manaraa.com

of the pipeline system. The Rocky Mountain region, PADD IV, has the smallest and fastest-growing oil market in the U.S., with only 3% of national petroleum product consumption. The West Coast region (PADD V) is geographically separated from the rest of the country by the Rocky Mountains, which makes its oil supply logistics independent of other regions.

Data

This study focuses on oil refiners' production decisions. We assume that for a given ownership structure, net gasoline import, and crude oil price, refiners make production decisions prior to production runs so as to maximize expected profits contingent upon the short-run capacity limitation, inventory levels, and unrealized supply disruption. The short-run distillation capacity and inventory levels are costly to adjust. To examine the impacts of ethanol production on gasoline prices and refinery profits, we employ the crack ratio and crack spread as dependent variables in this study.

The crack ratio (π_{CR}), which is defined as the gasoline price relative to that of crude oil, is calculated as

$$\pi_{CR} = \mathrm{P}_G * 42/\mathrm{P}_O \tag{4.1}$$

where P_G is the average wholesale gasoline price (dollars per gallon) for all grades,[2] and P_O is the U.S. crude oil composite acquisition cost by refiners (dollars per barrel).

The 3-2-1 crack spread (π_{CS}) is defined as

$$\pi_{CS} = \frac{2}{3}\mathrm{P}_G * 42 + \frac{1}{3}\mathrm{P}_H * 42 - \mathrm{P}_O \tag{4.2}$$

where P_H is the wholesale price of No. 2 distillate fuel (dollars per gallon). All prices are from monthly data obtained from the EIA website. The crack spread, π_{CS}, is deflated by the Producer Price Index (PPI) for crude energy material. The PPI data are obtained from the website of the U.S. Bureau of Labor Statistics.

[2]Using regional spot prices of Reformulated Gasoline Blendstock for Oxygen Blending (RBOB), which is a motor gasoline blending component that has no oxygenates blended including fuel ethanol, we get similar estimation results. See the Appendix A.1.

المنارة للاستشارات
www.manaraa.com

Crude oil and gasoline prices are closely related, as they are the raw material and the final product of the refining process. EIA refinery yield data shows that crude oil is the dominant input into the refinery, and that gasoline accounts for on average 47% of U.S. refinery output. The crack ratio is found to be empirically consistent and well suited to econometric analysis as a measure of refinery margins (Brown and Virmani 2007). The 3-2-1 crack spread has been institutionalized over the years as an alternative indicator of the refinery margins. Gasoline and distillate fuel oil are the two primary products of the refining industry, together comprising about 80% of refinery yield. The relative proportion of these two products is approximately two barrels of gasoline to one barrel of distillate fuel from three barrels of crude oil. Figures 4.1 and 4.2 present the monthly crack ratio and deflated 3-2-1 crack spread for five PADD regions over the period of 1995-2008. The graphs present similar seasonal and non-seasonal patterns for the crack ratio and the 3-2-1 crack spread.

Monthly dummy variables are incorporated to control for seasonal patterns. The non-seasonal patterns of the indices are controlled for by demand and supply conditions, the complexity adjusted distillation capacity, market concentration, unexpected supply disruptions, gasoline imports, and ethanol production. Summary statistics for these variables can be found in table 4.1. Each of these chosen variables and its relationship with refinery profitability are discussed next.

Seasonality

Heavily influenced by gasoline markets, U.S. refining profit margins are highest in the spring and summer (EIA 1996), because of strong demand induced by seasonal driving patterns. Demand for distillate fuel, including heating oil and diesel fuel, typically peaks in winter and thus exhibits a counter-cyclical price pattern with gasoline. Distillates have a smaller volume and hence a smaller influence on refining profit. Therefore, the crack ratio and the crack spread show seasonal swings corresponding to price variation in the gasoline market. The refining margin is typically lowest during the winter months when gasoline demand and prices fall and inventories are building, and is highest in summer months.

المنارة للاستشارات
www.manaraa.com

Crude and Product Market Conditions

We hypothesize that gasoline prices and refinery profits are impacted by supply and demand balances in crude oil and refinery product markets. When stocks in the crude oil market are high, refinery profits should increase because of lower input costs. Alternatively, when there are large stocks of gasoline and other refinery products, refinery profits should fall. A tight product market will generate upward pressure on product prices even when there is an ample supply of crude oil. Product prices will be bid up by more than any underlying crude price increase. This upward movement relative to crude oil prices will show up as an increase in the corresponding crack ratio and crack spread. Crude oil and gasoline stocks not only provide a cushion between major short-term supply and demand imbalances but also indicate price pressures. Monthly crude oil ending stocks excluding the Strategic Petroleum Reserve (SPR) and total motor gasoline ending stock data were downloaded from the EIA website.

Complexity Adjusted Refinery Capacity

Refinery capacity is an indicator of the refining industry's ability to satisfy demand. Downstream processing facilities extend a refiner's flexibility to adjust its product slate in order to meet market demand for high-quality refinery products and changing environmental regulations. The production flexibility in turn improves the refinery's efficiency and results in a reduction in variable costs and an increase in refinery margin. The downstream facilities include fluid catalytic cracking (FCC), hydrocracking, coking, and other residual conversion facilities that convert the heavy material in crude oil to lighter, higher-valued products such as gasoline and diesel.

We employ regional equivalent distillation capacity (EDC), which is a complexity-adjusted measurement of a refiner's total production capacity and is used commonly in the refining industry as a normalized measure of production. Annual EDC for region i is calculated as

$$\mathrm{EDC}_i = \sum_{j=1}^{n} c_j \cdot M_{ij} \quad i = 1, ..., 5, j = 1, ..., n. \tag{4.3}$$

where $c_j, j = 1, ..., n$ is the Nelson's complexity index (Nelson 1976,1978) for downstream

المنارة للاستشارات
www.manaraa.com

processing unit j. $M_{ij}, i = 1, ...5$ are production capacities of the corresponding processing units in region i.

The Nelson complexity index is a measure of secondary conversion capacity in comparison to the primary distillation capacity. It is an indicator of the value addition potential of a refinery, in which a factor 1 is assigned to the atmospheric distillation unit. We consider six ($n = 6$) downstream processing units: vacuum distillation, thermal cracking, fluid & delayed coking, catalytic cracking, catalytic reforming, and catalytic hydrotreating units. Complexity indices of these downstream units are shown in table 4.2. Regional level capacity data are collected from the EIA website whereby capacity of each process is measured by barrels per steam day, which is the volume of inputs that can be processed when running at full capacity under optimal conditions. Figure 4.3 presents annual EDC for five PADD regions for 1995-2007. Total EDC in the U.S. increased by 22% over the past twelve years, with PADD III, the Gulf Coast, having the highest growth of 30%. The lowest increase in EDC occurred in the West Coast, with a 10% growth over the same period.

Refinery Market Concentration

Mergers and acquisitions among refinery firms may potentially reduce competition in the refinery market leading to higher refinery margins. To measure the level of market concentration, the common Herfindahl-Hirschman Index (HHI) is applied in the study. The annual HHI of a specific refinery market is calculated as

$$\text{HHI}_t = \sum_{i=1}^{N_t} S_{it}^2 \tag{4.4}$$

where S_{it} is the market share of a specific refiner in the corresponding market with total refinery firms of N_t at year t. A market with an HHI less than 1,000 is considered to be a competitive market; 1,000-1,800, a moderately concentrated market, and greater than 1,800, a highly concentrated market (GAO 2004).

We constructed HHIs for the individual PADD regions over the period of 1995-2007, which are presented in figure 4.4. The HHI for the refinery market in PADD I increased from 1,558 to 2,335 from 1995 to 2007 and changed from a moderately concentrated to a highly concentrated

المنارة للاستشارات
www.manaraa.com

market. Since much of this region's refinery product supply is from other regions, the impact of this increased concentration may be small. The refinery market in PADD II, the Midwest, suggests that this is a competitive market, although its HHI increased to 960 in 2007. Similarly, PADD III, the Gulf Coast, also has a competitive refinery market as of the end of 2007. The HHI for PADD IV, the Rocky Mountains, decreased from 1,025 to 930, which suggests that its refinery market became less concentrated than before. The HHI for PADD V, the West Coast, increased from 914 to 1,155, and this refinery market changed to a moderately concentrated market by 2007.

Unexpected Supply Disruptions

On August 29, 2005, Hurricane Katrina hit the U.S. Gulf Coast at New Orleans. On September 24, 2005, Hurricane Rita hit at the border between Texas and Louisiana. Both were category four storms when they did significant damage to the refineries' facilities and pipeline in the Gulf Coast region. Refinery operations were reduced by 1.8 million barrel per day in September and October 2005. Retail gasoline prices were distinctly higher than before and jumped by \$0.50 to over \$3.00 per gallon on a national average basis after Hurricane Rita. In order to control for the effect of this event on the gasoline price and refinery margin, we include dummy variables for September and October of 2005, when the disruptions were most severe.

Gasoline Imports

A significant share of total gasoline demand in the U.S. is met by imports. The net import share of total gasoline consumption in 2007 is 14%. Major sources of gasoline imports include Canada, Europe, and the Virgin Islands. A structural surplus in gasoline production in Europe means that gasoline production costs are lower when derived from foreign sources than they would be if the U.S. built and operated additional refinery capacity domestically. Growth in imports is expected to be tempered because of the increased use of domestically produced ethanol. Also, refinery profitability is expected to be negatively affected by increases in imported gasoline. Monthly finished motor gasoline imports from all countries of individual

المنارة للاستشارات
www.manaraa.com

regions are included in this study. The data were downloaded from the EIA website.

Gasoline imports is likely to be endogenous as included and may possibly lead to inconsistent estimates. One solution is to find legitimate instruments, which need to be uncorrelated with the current error term and correlated with the dependent variables. Two sets of instrumental variables are chosen to deal with the possible endogeneity problem: (1) the one-month lagged individual region imports, and (2) one- and two-month lagged price difference between the U.S. refinery region and the Amsterdam-Rotterdam-Antwerp (ARA) refining hub. The latter is more reflective of the prices in inland European market. We hypothesize that the monthly regional gasoline imports are considered to be dynamically adjusted according to the gasoline price difference between local and international markets.

In the first stage of IV estimation, fitted regional gasoline imports are obtained from the following regression and used as the exogenous variable in the final regression.

$$Import_{i,t} = \alpha + \beta\ Import_{i,t-1} + \delta_1\ dP_{i,t-1} + \delta_2\ dP_{i,t-2} \tag{4.5}$$

where $Import_{i,t}$ represent imports of gasoline to the U.S. regional refinery market, PADD i, at month t, $dP_{i,t-1}$ and $dP_{i,t-2}$ are the one- and two-month lagged price differential of the conventional regular gasoline between region i and ARA. Given the instrument's validity, the Davidson-MacKinnon's exogeneity test (F test) statistic (Davidson and Mackinnon 1993, p. 237) is 4.22 (7.33) for the crack ratio (crack spread) and the null hypothesis of exogeneity is rejected at 5% (1%) significance level.

Ethanol Production

There are approximately 161 ethanol plants in service in 2008 compared to 68 plants in 2003, with a production capacity of 9.357 million gallons per year (mgy) (RFA 2008). An additional 49 plants are under construction or expanding and these will bring the total up to 13.645 billion gallons. Since most of the nation's corn is produced in the Midwest, ethanol plants have been concentrated within this region. Iowa produces about 30% of the nation's ethanol and has two to three times as much production capacity as neighboring states. Our hypothesis is that this additional production has had a negative impact on gasoline prices and on the margins of

المنارة للاستشارات
www.manaraa.com

crude oil refiners. Monthly U.S. fuel ethanol production data were downloaded from the EIA website and employed in this study.

Estimation

In this section, we consider the estimation based on panel data of five PADD regions over the period of January 1995 to March 2008. Various stationarity/unit root tests are applied on data series of the crack ratio and crack spread to understand their time-series properties.

The Levin-Lin-Chu test (Levin, Lin, and Chu 2002), hereafter denoted by LLC, and the Im-Pesaran-Shin test (Im, Pesaran, and Shin 2003), hereafter denoted by IPS, and the cross-sectionally augmented Dickey-Fuller test (Pesaran 2007), hereafter denoted by CADF, are applied on the panel data of the crack ratio and crack spread. Under the null hypothesis, all three tests assume that all series in the panel are non-stationary processes against the alternative that all series are stationary. The LLC test is applicable for homogeneous panels, where the autoregressive coefficients for unit roots are assumed to be the same across sections. The IPS test allows for heterogeneous panels. But both the LLC and IPS tests assume that the individual processes are cross-sectionally independent. The CADF test can be applied to heterogenous panels with cross-sectional dependence. Baltagi, Bresson, and Pirotte (2007) point out that panel unit root tests like the CADF test, which explicitly allow for cross-sectional dependence, have better performance than other classical panel unit root tests that assume cross-sectional independence. The test results in table 4.3 show that the null hypotheses of non-stationarity are rejected at the 1% significance level, which indicates that both the crack ratio and 3-2-1 crack spread are level stationary.

In addition, refinery margin is liable to exhibit lagged behavior over time. It may be reasonable to assume that observations on the same region in consecutive time periods are correlated. Applying the Wooldridge test for autocorrelation in panel data for the crack ratio (crack spread) (Wooldridge 2002, p. 282), we get F-test statistics of 237.11 (272.20), which are highly significant, and the null hypotheses of no first-order autocorrelation are rejected.

Next, we account for heterogeneity across regions by using the fixed effects estimator. To

المنارة للاستشارات
www.manaraa.com

justify the fixed effects model, the Hausman test for misspecification (Greene 2003, p. 301) is employed. Under the null hypothesis, the random effects estimator is consistent and efficient, while under the alternative, it is inconsistent. The fixed effects model is chosen if we reject the null hypothesis. In the case of the crack ratio (crack spread), the χ^2 test statistic is calculated as 77.25 (102.76) and is significant at the 1% level. This suggests that the fixed effects estimator is consistent and asymptotically efficient in both cases. Results of a modified Wald test for groupwise heteroskedasticity (Greene 2003, p. 323) in a fixed effects panel data model indicate that the null hypothesis of homoskedastic disturbances was rejected at the 1% significe level with χ^2 test statistic 157.36.

Based on the above specification test results, we employ a fixed effects panel data model with correction for first-order serial correlation and groupwise heteroskedasticity. The panel data regression model is specified as:

$$\begin{aligned} \pi_{it} &= \alpha_i + X_{it}^{'}\beta + \varepsilon_{it} \\ \varepsilon_{i,t} &= \rho\varepsilon_{i,t-1} + \phi_{i,t}, \quad \phi_{i,t} \sim N(0, \sigma_{\phi_i}^2) \end{aligned} \tag{4.6}$$

where $i = 1, ..., N$ denotes the cross-section dimension, the PADD regions, and $t = 1, ..., T$ denotes the time-series dimension. The autocorrelation coefficient $\mid \rho \mid < 1$ and $\phi_{i,t}$ is independently distributed with zero mean and region-specific variance $\sigma_{\phi_i}^2$. π_{it} is the crack ratio or the 3-2-1 crack spread on the ith region for the tth time period. X_{it} is the K-dimensional vector of explanatory variables defined earlier, in which regional gasoline imports are instrumented by employing equation (4.5). Expression α_i represents the regional fixed effect. After stacking the n time series,

$$\pi_i = \alpha_i + X_i\beta + \varepsilon_i \quad i = 1, ..., n.$$

Each submatrix has n observations. We also specify $E(\varepsilon_i|X) = 0$ and $E(\varepsilon_i\varepsilon_j^{'}) = \sigma_{ij}\Omega_{ij}$.

المنارة للاستشارات
www.manaraa.com

Collecting the terms above, we have the full specification,

$$E(\varepsilon|X) = 0 \quad \text{and} \quad E(\varepsilon\varepsilon') = \Omega = \begin{bmatrix} \sigma_{11}\Omega_{11} & \sigma_{12}\Omega_{12} & \dots & \sigma_{1N}\Omega_{1N} \\ \sigma_{21}\Omega_{21} & \sigma_{22}\Omega_{22} & \dots & \sigma_{2N}\Omega_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1}\Omega_{N1} & \sigma_{N2}\Omega_{N2} & \dots & \sigma_{NN}\Omega_{NN} \end{bmatrix}$$

where

$$\Omega_{ij} = \begin{bmatrix} 1 & \rho_j & \rho_j^2 & \dots & \rho_j^{T-1} \\ \rho_i & 1 & \rho_j & \dots & \rho_j^{T-2} \\ \rho_i^2 & \rho_i & 1 & \dots & \rho_j^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_i^{T-1} & \rho_i^{T-2} & \rho_i^{T-3} & \dots & 1 \end{bmatrix}.$$

Taking into account serial correlation and groupwise heteroskedasticity, a two-step, feasible, efficient Generalized Method of Moments (GMM) estimator (Baum et al. 2007; Schaffer 2007) is obtained through the following estimation procedure.

(a) Estimate Equation (4.6) using pooled OLS to get initial estimates $\hat{\beta}_0 = (X'X)^{-1}X'\pi$.

(b) Form the residual $\hat{u} = \pi - X\hat{\beta}_0$ and use these to form the optimal weighting matrix $\hat{W} = \hat{S}^{-1}$, which minimizes the asymptotic variance of the GMM estimator.

(c) Calculate the efficient GMM estimator $\hat{\beta}_1$ and corresponding variance-covariance matrix $V(\hat{\beta}_1)$ using the estimated optimal weighting matrix $\hat{W}$ in step (b). We get

$$\begin{aligned} \hat{\beta}_1 &= (X'X\hat{W}X'X)^{-1}X'X\hat{W}X'\pi \\ V(\hat{\beta}_1) &= \frac{1}{n}(\bar{Q}'\hat{W}\bar{Q})^{-1} \quad \text{where} \quad \bar{Q} = \frac{1}{n}X'X \end{aligned} \tag{4.7}$$

In step (b), $\hat{S}$ is estimated as

$$\hat{S} = \hat{\Gamma}_0 + \sum_{j=1}^{q} \kappa(\frac{j}{q_n})(\hat{\Gamma}_j + \hat{\Gamma}_j'),$$

المنارة للاستشارات
www.manaraa.com

where $\hat{\Gamma}_j = \frac{1}{n}\sum_{t=1}^{n-j} X_t' \hat{u}_t \hat{u}_{t-j} X_{t-j}$ are the sample autocovariance matrices for lag j computed using consistent residuals $\hat{u}_t$ from step (a). The kernel function, $\kappa(j/q_n)$, applies appropriate weights to the summations, with q_n defined as the bandwidth of the kernel. The Bartlett kernel function proposed by Newey and West (1987) is employed as

$$\kappa(\cdot) = \begin{cases} 1 - \frac{j}{q_n} & \text{if } j \leq q_n - 1 \\ 0 & \text{otherwise} \end{cases}$$

in our estimation. These estimates are said to be heteroskedasticity and autocorrelation consistent (HAC) and are presented in table 4.4.

The crack ratio and crack spread are closed related as both are indicators of refiners profit margin. It has been shown that joint estimation of two equations as a system of seemingly unrelated regressions (SUR) to account for contemporaneous correlation may improve estimation efficiency (Greene 2003, Ch. 14). In the joint estimation, error structures of the crack ratio and crack spread equations are assumed to be characterized by panel heteroskedasticity, first-order panel autocorrelation, and contemporaneous correlation. The regional gasoline imports are instrumented using equation (4.5). Following the estimation framework suggested by Blackwell (2005), the panel SUR estimation results are presented in table (4.5).

Analysis of Estimation Results

The estimations for the crack ratio and 3-2-1 crack spread yield similar results, and all explanatory variables have intuitive signs. Crude oil inventories, ethanol production, short-run supply disruptions, market concentration represented by the HHI index, monthly gasoline import, and dummy variables for months in the second and third quarters all significantly influence the crack ratio and the 3-2-1 crack spread. The complexity adjusted distillation capacity has a marginally significant and positive impact on the crack ratio. Higher crude oil inventories, the spring and summer travel seasons, and historical short-term supply disruptions all lead to higher levels of the crack ratio and the crack spread.

As expected, both ethanol production and gasoline import have considerably negative impacts on the refinery margin, and the impacts are significant at the 1% level. This indicates

المنارة للاستشارات
www.manaraa.com

that over the sample period, ethanol has a significant substitution effect on gasoline. Evaluating at the sample mean, the wholesale gasoline price is found to be lowered by 14¢/gallon because of ethanol production. Furthermore, ethanol production reduces the crack spread, which indicates a reduction in refinery profits. At the average production level over the sample period, the reduction in the crack spread due to ethanol production is estimated to be $1.33 per barrel.

The panel SUR estimation results in table (4.5) indicate consistent estimates for all the explanatory variables except the equivalent distillation capacity and HHI index. In the joint estimation, market concentration level are not significant in explaining the variation in both gasoline price and refiners profitability, while EDC appears to have significant and positive effects on both dependent variables.

Regional Analysis

To further investigate the negative effect of ethanol production on local retail gasoline prices, it is instructive to analyze the time-series data of each region individually. Note that we have switched from wholesale to retail prices for this portion of the analysis. We do this because weighted retail prices represent local market conditions better than regional wholesale prices that often represent one or two unique points in each region. The use of retail prices also assists in the use of our results for policy purposes.

However there is an obvious problem with our use of retail prices. As we haven mentioned earlier typical ethanol blends contain only 96.81% of the energy as regular gasoline. Therefore one would expect that as more gallons of ethanol blend are sold then weighted retail prices will eventually reflect this lower energy content. This comparison is complicated by differences in state level subsidies to ethanol and by different local market conditions and regulations. For example in some states ethanol is viewed as a way to improve the oxygenate level in gasoline and as such it may not require a price reduction to clear this market. In other states all regular gasoline is an ethanol blend. We did run the national model using national retail prices and these results suggested that the national retail impact is 39¢ per gallon with signs

المنارة للاستشارات
www.manaraa.com

and significance levels that are very similar to the national wholesale analysis described above.[3]

Each PADD region has unique supply and demand conditions of crude oil and refinery products, different market structures and ethanol production and usage. The effects of explanatory variables may differ considerably because of region-specific factors. The results of a Durbin-Watson test and Box-Ljung Q test for autocorrelation (Greene 2003, p. 268-271) indicate the presence of autocorrelation.[4] Using the regional crack ratios as dependent variables, the estimated coefficients for individual regions' monthly data over January 1995 to March 2008 are reported in table 4.6.[5]

From the estimation results, ethanol production has significant and negative effects on retail gasoline prices in all regions. And the magnitude of the effects varies with PADD regions, ranging from -0.000016 to -0.000063. As expected, in PADD II, the Midwest, ethanol production has the largest impact on retail gasoline prices. The substitution effect is highly significant and reduces the gasoline price by 34¢ per gallon on average over the sample period. The West Coast and East Coast experience similar negative ethanol impacts with estimates of -0.000055 and -0.000052, which means that the corresponding gasoline price is lowered by 26¢ and 23¢ per gallon, respectively. The Gulf Coast, PADD III, has a coefficient estimate of -0.000045, or, equivalently, a 20¢ per gallon reduction in retail gasoline prices. The Rocky Mountain, or PADD IV, experienced the smallest downward gasoline price change, at 6.7¢ per gallon, presumably because of this region's comparatively low total ethanol consumption.

Welfare Analysis

In the following section, based on the estimated substitution effect of ethanol on gasoline in 2007, we develop an analytical model explicit in its accounting of ethanol, gasoline, and fuel markets.[6] We estimate the welfare impacts on agricultural and energy markets, and on overall welfare change after accounting for reduced loan deficiency payments. The welfare changes are

[3] See the Appendix A.2.

[4] Test results for autocorrelation are in the Appendix A.3.

[5] In regional regressions, regular retail gasoline prices are used to construct the variable of regional crack ratio. Using average wholesale gasoline data of individual regions, we only found significant negative substitution effects on gasoline in PADD I, II, and V of 8.5¢, 15.4¢, and 12.9¢, respectively.

[6] Fuel refers to gasoline blended with ethanol used for transportation.

المنارة للاستشارات
www.manaraa.com

estimated by both traditional consumer (producer) surplus formulas and compensating variation measure. Then, we validate the model's underlying assumptions and test for sensitivity of the main results to market parameters.

The Analytical Model

In the model, the corn market includes ethanol and non-ethanol demand and corn supply. The fuel market includes gasoline and ethanol separately to disentangle the relationship between these markets and better capture the substitution effect of ethanol on gasoline. We provide graphical illustration of the corresponding welfare changes in terms of consumer and producer surplus. This study does not explicitly evaluate the impact of the import tariff or the consumption mandate. We do this because the import tariff is so similar in magnitude to the blenders credit. Imported Brazilian ethanol is subject to the 54¢ import tariff but it then benefits from the 51¢ blenders credit these two approximately offset each other. We ignore the ethanol mandate because it was not binding in the base period because high energy prices encouraged ethanol production to grow beyond the ethanol mandate that was in place that year. Also we have not considered the impact of induced higher prices of other crops. It seems likely that consumers of these other crops lost and that producers gained as a result of ethanol subsidies. There was also a reduction in government loan deficiency payments to these producers. We also ignore the possible environmental benefits or costs of ethanol production and consumption.

Corn Market

Consider the standard supply and demand model for corn graphically depicted in figure 4.5 where S_C is the supply schedule and D_C^{ne} represents non-ethanol demand for corn including feed, export, and other consumption. The equilibrium price and quantity are P_C and Q_C, respectively. In this original equilibrium, given the loan rate in the 2002 Farm Security and Rural Investment Act of 2002 (FSRI), corn producers receive a price of P_{LR} for each bushel of corn produced, yielding a total production of Q_{LR} bushels and the market clears at price

المنارة للاستشارات
www.manaraa.com

P_0. The loan deficiency payments (LDPs) program generates producer surplus of $P_{LR}C'DP_C$, consumer surplus of $P_CDB'P_0$, and taxpayer costs of $P_{LR}C'B'P_0$, which add up to a deadweight loss of the area $C'DB'$.

Increasing demand for ethanol production pushes up the equilibrium corn price to $P_C^{'}$, which is higher than the loan rate P_{LR}. This higher equilibrium price results in the corn production of $Q_C^{'}$, while non-ethanol demand drops to $Q_C^{''}$. The amount of corn represented by the distance of $Q_C^{'} - Q_C^{''}$ is used for ethanol production. Under price $P_C^{'}$, the total corn demand curve including ethanol is D_C. The total gain for producer is represented by the area $ACC^{'}P_{LR}$, while the loss of consumer surplus is the area $ABB^{'}P_0$. The taxpayer cost of moving the corn demand curve out is considered within the energy market because it appears in the form of a blenders tax credit. In addition, this higher equilibrium corn price eliminates the LDPs to farmers. The corresponding welfare gain for taxpayers is the shaded area $P_{LR}C^{'}B^{'}P_0$ in figure 4.5.[7]

Ethanol, Gasoline, and Transportation Fuel Markets

The markets for ethanol, gasoline and fuel are in the left and right panels of figure 4.6. The horizontal axis is measured in gallons of gasoline equivalent and the vertical axis is measured in the price of gasoline (or fuel) because that the energy of 2.66 gallons of ethanol is equivalent to 1.74 gallons of gasoline. That is we measure the quantity of ethanol in 0.65 gallon units. When we measure the blenders tax credit in energy equivalence it is equal to 78¢ per gallon. Demand for non-fuel ethanol and total ethanol supply are represented by D_e^{nf} and S_e, respectively, and appear backwards in the left panel of figure 4.6. We assume the U.S. non-fuel ethanol demand is perfectly inelastic because demand for unadulterated ethanol is used primarily in medicine and very small, at 380 million gallons in 2007.

In the right panel of figure 4.6, supply in the gasoline market is given by S_g. Without the ethanol tax credit t, equilibrium prices are P_e^{nf} and P_g in the two respective markets. Ethanol demand for fuel use is zero at this original equilibrium price. The amount of ethanol that will

[7]Averaged over 2005 and 2006, the LDPs for corn is about 81% of total payments.

المنارة للاستشارات
www.manaraa.com

be supplied for fuel at higher price than P_e^{nf} is given by the excess supply curve XS_e. The 51¢ federal tax credit t (or 78¢ in gasoline equivalent unit) has the effect of shifting the demand for ethanol to $D_e^{'}$. The intersection of demand and supply curves leads to the new equilibrium ethanol price of P_e^f, at which the excess supply of ethanol used in fuel is represented by FH ($= P_e^f H'$ on the excess supply curve in the right panel). In the ethanol market, producers gain is represented by the hatched area $FP_e^f P_e^{nf} G$ and consumer surplus doesn't change because the non-fuel ethanol demand curve is vertical.

We shift down the excess supply curve of ethanol by the amount of the tax credit t to $XS_e^{'}$. The new fuel supply curve is S_f with the amount of ethanol $P_f I$ ($= P_e^f H'$) and gasoline $P_f J$. The resulting equilibrium fuel price is P_f. Gasoline use is reduced by the amount of JL, which is substituted by ethanol, and fuel consumption is increased by the distance of LK because of the lower price of fuel. In the total fuel demand of $P_f K$, the amount of JK is met by ethanol, which is equal to the amount of $P_f I$. Gasoline producers lose the area $P_g MJP_f$ and fuel consumers gain the area $P_g MKP_f$. The net change of consumer and producer surpluses is represented by the hatched area MKJ. The amount of government payments for ethanol tax credit is represented by the shaded area $P_e^f H' IP_f$. The producer surplus in the ethanol market is the shaded area FHG in the left panel of figure 4.6. We assume that the non-fuel ethanol demand is negligible compared with fuel ethanol production.

The total ethanol tax credit t consists of three components: (1) the reduction in fuel price because of ethanol substitution denoted by $P_g - P_f$; (2) the price change in the ethanol market, $P_e^f - P_e^{nf}$; (3) the price difference between P_e^{nf} and P_g. The prices change of $P_e^f - P_e^{nf}$ represents the "wasted" portion of the tax credit, which is used to make the ethanol production economically feasible and referred as "water" (de Gorter and Just 2007). Although qualitative relations exist among these three components, the specific cut-off points vary over time and critically depend on corn and crude oil price.

المنارة للاستشارات
www.manaraa.com

Welfare Estimates

Given the annual market data and assumed parameters, as shown in table 4.7, the net welfare loss in the U.S. corn market is approximately \$2.12 billion, as presented in table 4.8. The welfare gain from the reduced LDPs for corn are \$3.45 billion according to the average actual payments of 2005 and 2006.[8] The change of producer surplus in the ethanol market is about \$0.86 billion, while the net welfare change before the government cost of the ethanol credit is estimated to be \$0.79 billion in the gasoline/fuel market. Ethanol production in 2007 provided a benefit to corn, ethanol producers and gasoline/fuel consumers. It reduced welfare for grain consumers and gasoline refiners. The overall net welfare loss is approximately \$0.28 billion.

The basic parameters assumed for U.S. corn and gasoline markets are summarized in table 4.7. In the corn market, the elasticity of demand is assumed to be -0.15 with range of -0.10 to -0.20, while the elasticity of supply is 0.27 ranging and ranges from 0.13 to 0.40. We take these parameters from Elobeid and Tokgoz (2008).[9] The short-run gasoline elasticities of demand is -0.35 with the range of -0.2 to -0.5 and that of supply is 0.25 varying from 0.1 to 0.4 The elasticity parameters in the gasoline market are based on the survey of Graham and Glaister (2002).

We calibrate the model to 2007 market data of price and production, which are also reported in table 4.7. There are three important price changes for the welfare analysis including (1) the reduction in fuel price, $P_g - P_f$, which is about 23¢ using estimated coefficient in the empirical analysis; (2) the increase of corn price, $P_C^{'} - P_C$, which is \$1.27 reported in Tokgoz et al. (2007); (3) the price change in ethanol market, $P_e^f - P_e^{nf}$. We use average weekly ethanol prices of Chicago in 2005 and 2007 to proxy P_e^f and P_e^{nf}, respectively, which results in the ethanol price change of 27¢ (or 41¢ in gasoline equivalent units). The ethanol weekly prices are obtained from Ethanol and Biofuel News.

[8]The actual LDPs data are obtained from the CCC Budget Essentials of the Farm Service Agency (FSA) http://www.fsa.usda.gov/FSA/webapp?area=about&subject=landing&topic=bap-bu-cc, last visited 10/08/2008.

[9]We use the ranges of demand and supply elasticities in the following section to test for sensitivity of the welfare estimates.

المنارة للاستشارات
www.manaraa.com

Sensitivity Analysis

Gardner and Tyner (2008) point out that elasticity assumption is critical for the evaluation of welfare changes since these parameters summarize the price responsiveness to policy interventions. In order to test for the sensitivity of our welfare estimates on these assumptions, we evaluate the overall welfare changes for the given ranges of demand and supply elasticities of corn and gasoline markets. The results are depicted in figures **??** and **??**. The net welfare loss varies from \$0.05 billion to \$1.19 billion as corn demand and supply elasticities vary in the given ranges. Similarly, the net welfare loss is in the range of \$0.02 billion to \$0.79 billion as elasticities of gasoline change.

It is known that ordinary consumer surplus measure requires a restrictive path-independence condition on the utility function and constant marginal utility of income so as to ensure its uniqueness as a money measure (Just, Hueth, and Schmitz 2004, p. 136). Compensating and equivalent variation is the recommended alternative and provides measures related to actual changes in utility. Following the indirect estimation method developed in Willig (1976) and Just, Hueth, and Schmitz (2004, Section 6.5), we calculate the approximate compensating variations in corn and gasoline markets. These approximations are based on the income elasticities and disposable personal income of 2007 as reported in table 4.7 and the approximation formula:

$$\widehat{\mathrm{CV}} = \triangle\mathrm{CS}(1-\hat{\delta}); \quad \hat{\delta} = \frac{\eta|s|}{2}; \quad s = \frac{\triangle\mathrm{CS}}{m}. \tag{4.8}$$

where the compensating variation is denoted by CV, $\triangle$CS is the change in consumer surplus. η represents the income elasticity of demand while disposable personal income is m. The approximation results are presented in table 4.8. Because of the small ratio of surplus change to total income (< 0.01 in both cases) and income elasticity, the difference between two consumer welfare measures are very small. The estimated total net welfare loss based on the compensating variation measure is about \$0.30 billion.

المنارة للاستشارات
www.manaraa.com

Conclusion

Accounting for temporal autocorrelation and regional heterogeneity, we employ a fixed effects panel data model to quantify the possible impact of ethanol on gasoline in the U.S. as a whole and in five regions of the U.S. Estimation results show a significant negative effect of increasing ethanol production on wholesale gasoline prices. In addition, the impact on retail gasoline prices varies considerably across regions, with the largest impact of 34¢/gallon in the Midwest. Refinery market concentration is found to significantly increase the gasoline price and the refinery margin. It is also found that increasing downstream processing capacity is marginally significant in explaining changes in gasoline prices. The results also suggest that the ethanol-induced reduction in gasoline prices came at the expense of refiners' profits, of approximately $1.33 per barrel.

These reductions in retail gasoline prices are surprisingly large, especially when one considers that they are calculated at their mean values over the sample period. The availability of ethanol essentially increased the "capacity" of the U.S. refinery industry and in so doing prevented some of the dramatic price increases often associated with an industry operating at close to capacity. Because these results are based on capacity, it would be wrong to extrapolate the results to today's markets. Had we not had ethanol, it seems likely that the crude oil refining industry would be slightly larger today than it actually is, and in the absence of this additional crude oil refining capacity, the impact of eliminating ethanol would be extreme.

Government support policies coupled with high energy prices stimulated a rapid increase in ethanol production and associated welfare transfers in multiple markets. We find that the net welfare change of the U.S. ethanol subsidy is negative, a result that is robust with respect to a reasonable range of alternative parameter values. The markets for agricultural commodities were not competitive prior to large-scale ethanol production because there was already significant intervention in the form of farm subsidies. Our results show that subsidizing U.S. ethanol production generated a small aggregate welfare loss, while also reducing the distortion associated with farm payments.

Our research suggests the need for future research in the following areas. First, the relation-

المنارة للاستشارات
www.manaraa.com

ship among crude oil, ethanol, gasoline, corn, and food prices needs further investigation. Corn prices have traditionally been affected by energy prices through production costs. Empirical analysis of linkages between energy and agricultural sectors has important policy implications in terms of the negative consequences of higher food prices. Second, as refinery economic performance becomes increasingly driven by heavy, sour crude oil coking processes, the 3-2-1 crack spread formula needs to be extended to more accurately reflect refinery profitability. This requires more detailed price and production cost information on different types of crude oil and refinery products. Finally, for the welfare analysis, incorporating other forms of government support policies such as ethanol mandates and import tariff is one of the future possible extensions. Also, further work on the global welfare impact of ethanol production appears necessary for better economic assessment of ethanol support policies.

المنارة للاستشارات
www.manaraa.com

Appendix

A.1. Fixed Effects Model Estimates Using RBOB Prices

	Crack Ratio		3-2-1 Crack Spread	
	Estimate	Robust Std. Err.	Estimate	Robust Std. Err.
Oil stock	9.70e-07*	5.60e-07	2.54e-09*	1.46e-09
Gasoline stock	-.000019***	5.49e-06	-6.04e-08***	1.75e-08
EDC	-1.64e-08	3.89e-08	-3.04e-12	1.42e-10
Ethanol production	-.000019***	6.65e-06	-5.16e-08***	2.25e-08
Gasoline import	.000010	7.30e-06	6.98e-09	2.94e-08
HHI	-.0015	.0016	-2.21e-06	5.56e-06
January	.078**	.034	.000034	.00011
February	.092**	.040	.00035**	.00014
March	.16***	.052	.00061***	.00018
April	.29***	.025	.00062***	.00013
May	.32***	.035	.00052***	.00015
June	.23***	.021	.00079***	.00012
July	.16***	.036	.00042**	.00018
August	-.0065	.032	-.00019	.00018
September	-.088***	.021	-.00048***	.00014
October	-.085	.027	-.00038**	.00015
November	-.053**	.022	-.00012	.00010
R^2	0.8748		0.8045	

Note: The STATA *xtivreg2* command with the robust and *bw* options is used. Single (*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively. Because of the availability of RBOB prices, only monthly data of PADD I, III, and V over the period of May 2006 - March 2008 are included.

المنارة للاستشارات
www.manaraa.com

A.2. Fixed Effects Estimates Using Retail Gas Prices

	Crack Ratio	
	Estimate	Robust Std. Err.
Oil stock	.000012***	3.52e-06
Gasoline stock	.000023***	1.91e-06
EDC	3.17e-08	9.09e-09
Ethanol production	-.000086***	9.55e-06
Supply disruption	.037	.078
Gasoline import	.000033***	9.87e-06
HHI	.00012	.00019
January	-.076***	9.55e-06
February	-.11***	.031
March	-.022	.037
April	.024	.044
May	.055	.052
June	.064	.046
July	.033	.041
August	.043	.033
September	.0079	.038
October	.0088	.034
November	-.024	.030
R^2	0.6282	

Note: The STATA *xtivreg2* command with the robust and *bw* options is used. Single (*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

المنارة للاستشارات
www.manaraa.com

A.3. Regional Autocorrelation Tests on Crack Ratio

	Durbin-Watson test	Box-Ljung Q test
PADD I	.635	377.40***
PADD II	.807	277.89***
PADD III	.646	509.25***
PADD IV	.294	646.15***
PADD V	.331	626.78***

Note: Single (*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

References

Adams, F.G., and J.M. Griffin. 1972. An Economic-Linear Programming Model of the U.S. Petroleum Refining Industry. *Journal of the American Statistical Association* 67: 542-551.

Asano H. 2002. An Empirical Analysis of Lumpy Investment: the Case of U.S. Petroleum Refining Industry. *Energy Economics* 24: 629-645.

Babcock, B.A. 2008. Distributional Implications of U.S. Ethanol Policy. *Review of Agricultural Economics* 30:533-542.

Bachmeier, L.J., and J.M. Griffin. 2003. New Evidence on Asymmetric Gasoline Price Responses. *The Review of Economics and Statistics* 85: 772-776.

Baltagi, B.H., G. Bresson, and A. Pirotte. 2007. Panel Unit Root Tests and Spatial Dependence. *Journal of Applied Econometrics* 22:339-360.

Baum, C.F., M.E. Schaffer, and S. Stillman. 2007. Enhanced Routines for Instrumental Variables/Generalized Method of Moments Estimation and Testing. *The Stata Journal* 7:465-506.

Blackwell, J.L. 2005. Estimation and Testing of Fixed-effect Panel-data Systems. *The Stata Journal* 5:202-207.

Blanch, F., S. Schels, G. Soares, M. Haase, and D. Hynes. 2008. Biofuels Driving Global Oil Supply Growth. *Global Energy Weekly*, Merrill Lynch.

Borenstein, S., and A. Shepard. 2002. Sticky Prices, Inventories, and Market Power in Wholesale Gasoline Markets. *Rand Journal of Economics* 33: 116-139.

المنارة للاستشارات
www.manaraa.com

Borenstein, S., C.A. Cameron, and R. Gilbert. 1997. Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes? *Quarterly Journal of Economics* 112: 305-339.

BP, 2008. Statistical Review of World Energy.

Brown, J., J. Hastings, E. Mansur, and S. Villas-Boas. 2008. Reformulating competition? Gasoline Content Regulation and Wholesale Gasoline Prices. *Journal of Environmental Economics and Management* 55:1-19.

Brown S., and R. Virmani. 2007. What's Driving Gasoline Prices? *Economic Letter* 2: 1-7. Federal Reserve Bank of Dallas.

Chen, M. 2002. Survival Duration of Plants: Evidence from the U.S. Petroleum Refining Industry. *International Journal of Industrial Organization* 20: 517-555.

Considine, T.J. 1992. A Short-Run Model of Petroleum Refining Industry. *The Energy Journal* 13: 61-91.

–. 1997. Inventories Under Joint Production: An Empirical Analysis of Petroleum Refining. *The Review of Economics and Statistics* 79: 493-502.

Davidson, R. and J. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.

de Gorter, H., and D.R. Just. 2007. The Welfare Economics of an Excise-Tax Exemption for Biofuels. MPRA Working Paper 5157, Department of Applied Economics and Management, Cornell University.

EIA (Energy Information Administration). 1996. Petroleum 1996: Issues and Trends.

–. 2007. Petroleum Supply Annual 2006. Available at: http://www.eia.doe.gov, last visited 01/20/2008.

–. 2008. Short-Term Energy Outlook, June 2008. Available at: http://www.eia.doe.gov/steo, last visited 01/20/2008.

Eidman, V.R. 2005. *Agriculture as a Producer of Energy*. In: K.J. Collins, J.A. Duffield, and J. Outlaw. Cambridge (Eds.), Agriculture as a Producer and Consumer of Energy. CABI Publishing, MA.

Elobeid A., and S. Tokgoz. 2008. Removing distortions in the U.S. ethanol market: what does it imply for the United States and Brazil. *American Journal of Agricultural Economics* 90:1-15.

Ethanol and Renewable Fuel News, Various issues, 2005-2008. Hart Energy Publishing, Houston, TX.

المنارة للاستشارات
www.manaraa.com

GAO. 2004. Energy Market: Effects of Mergers and Market Concentration in the U.S. Petroleum Industry. GAO Report 04-96.

Gardner, B. 2007. Fuel Ethanol Subsidies and Farm Price Support. *Journal of Agricultural & Food Industrial Organization* 5: Article 4.

Gardner, B., and W. Tyner. 2007. Explorations in Biofuels Economics, Policty, and History: Introduction to the Special Issue. *Journal of Agricultural & Food Industrial Organization* 5: Article 1.

Geweke, J. 2003. Empirical Evidence on the Competitive Effects of Mergers in the Gasoline Industry. Working Paper, University of Iowa.

Graham, D.J., and S. Glaister. 2002. The Demand for Automobile Fuel: A Survey of Elasticities. *Journal of Transport Economics and Policy* 36: 1-26.

Greene, W.H. 2003. *Econometric Analysis.* Prentice Hall, Upper Saddle River, NJ.

Griffin, J. 1972. The Process Analysis Alternative to Statistical Cost Functions: An Application to Petroleum Refining. *American Economic Review* 62: 46-56.

Im, K., M. Pesaran, and Y. Shin. 2003. Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics* 115:53-74.

Just, R., D.L. Hueth, and A. Schmitz. 2004. *The Welfare Economics of Public Policy, A Practical Approach to Project and Policy Evaluation.* Northamption, MA: Edward Elgar.

Kaufmann, R.K., and C. Laskowski. 2005. Causes for an Asymmetric Relation Between the Price of Crude Oil and Refined Petroleum Products. *Energy Policy* 33: 1587-1596.

Levin, A., C.F. Liu, and C. Chu. 2002. Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties. *Journal of Econometrics* 108:1-24.

Martinez-Gonzalez, A., I.M. Sheldon, and S. Thompson. 2007. Estimating the Welfare Effect of U.S. Distortions in the Ethanol Market Using a Partial Equilibrium Trade Model. *Journal of Agricultural & Food Industrial Organization* 5: Article 5.

Muehlegger, E. 2006. Gasoline Price Spikes and Regional Gasoline Content Regulations: A Structural Approach. KSG Faculty Research Working Paper Series RWP06-015, Harvard University.

Nelson, W.L. 1976. The Concept of Refinery Complexity. *The Oil and Gas Journal*, September 13, 81-82.

–. 1978. U.S. Refinery Complexity, 1909-1978. *The Oil and Gas Journal*, December 11, 106-108.

Newey, W.K., and K.D. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity

المنارة للاستشارات
www.manaraa.com

and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55: 703-708.

Oladunjoye, O. 2008. Market Structure and Price Adjustment in the U.S. Wholesale Gasoline Markets. *Energy Economics* 30: 937-961.

Pesaran, M.H. 2007. A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence. *Journal of Applied Econometrics* 22:265-312.

Pirog, R. 2005. Petroleum Refining: Economic Performance and Challenges for the Future. CRS Report for Congress.

Radchenko, S. 2005a. Lags in the Response of Gasoline Prices to Changes in Crude Oil Prices: the Role of Short-Term and Long-Term Shocks. *Energy Economics* 27: 573-602.

–. 2005b. Oil Price Volatility and the Asymmetric Response of Gasoline Prices to Oil Price Increases and Decreases. *Energy Economics* 27: 708-730.

RFA (Renewable Fuels Association). 2008. Industry Statistics. Available at: http://www.ethanolrfa.org/industry/statistics, last visited 01/20/2008.

Schaffer, M.E. 2007. XTIVREG2: Stata Module to Perform Extended IV/2SLS, GMM and AC/HAC, LIML and K-class Regression for Panel Data Models. Available at: http://ideas.repec.org/c/boc/bocode/s456501.html, last visited 01/20/2008.

Schmitz, A., C.B. Moss, and T.G. Schmitz. 2007. Ethanol: No Free Lunch. *Journal of Agricultural & Food Industrial Organization* 5: Article 3.

Taheripour, F., and W.E. Tyner. 2007. Ethanol Subsidies, Who Gets the Benefits? Paper Presented at Bio-Fuels, Food and Feed Tradeoffs Conference, April 12-23, St. Louis, Missouri.

Tokgoz, S., A. Elobeid, J.F. Fabiosa, D.J. Hayes, B.A. Babcock, T-H. Yu, F. Dong, C.E. Hart, and J.C. Beghin. 2007. Emerging Biofuels: Outlook of Effects on U.S. Grain, Oilseeds, and Livestock Markets. Staff Report 07-SR 101, Center for Agricultural and Rural Development, Iowa State University.

USDA/DOE. 2008. Letter to Senator Jeff Bingaman, Chairman of Senate Energy and Natural Resources Committee.

Vedenov, D.V., J.A. Duffield, and M.E. Wetzstein. 2006. Entry of Alternative Fuels in a Volatile U.S. Gasoline Market. *Journal of Agricultural and Resource Economics* 31: 1-13.

Wang, M., M. Wu, and H. Huo. 2007. Life-Cycle Energy and Greenhouse Gas Emission Impacts of Different Corn Ethanol Plant Types. *Environmental Research Letters* 2: 1-13. Available at: http://www.iop.org/EJ/abstract/1748-9326/2/2/024001/, last visited 01/20/2008.

المنارة للاستشارات
www.manaraa.com

Willig, R.D. 1976. Consumer's Surplus without Apology. *American Economic Review* 66: 589-597.

Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge. MIT Press, MA.

المنارة للاستشارات

www.manaraa.com

Table 4.1 Summary Statistics

Variable	Notation	Frequency	Level	Unit	Mean	Std. Dev.
Crude oil ending stock excluding SPR	Oil stock	Monthly	PADD	Thousand barrels	62131	53702
Total motor gasoline ending stock	Gasoline stock	Monthly	PADD	Thousand barrels	41491	20958
Equivalent distillation capacity	EDC	Annual	PADD	Barrels per steam day	3.08e+7	2.47e+7
Fuel Ethanol production	Ethanol Production	Monthly	National	Thousand barrels	5318	3519
Finished motor gasoline imports from all countries	Gasoline import	Monthly	PADD	Thousand barrels	2561	4827
Herfindahl-Hirschman Index	HHI	Annual	PADD		1118	446

Note: Monthly dummies for seasonality and short-term supply disruption are not included.

المنارة للاستشارات
www.manaraa.com

Table 4.2 Nelson Complexity Index of Downstream Processing Units

Processing unit	Nelson Complexity Index
Crude atmospheric distillation	1
Downstream operation:	
Vacuum distillation process	2
Thermal cracking	2.75
Fluid & delayed coking	6
Catalytic cracking	6
Catalytic reforming	5
Catalytic hydrotreating	3

Note: Because of data limitation, we only consider the above downstream processing units in the EDC calculation.

Table 4.3 Panel Unit Root Tests Results

Tests	Crack ratio	3-2-1 Crack spread
LLC	-10.25***	-12.33***
IPS	-5.04***	-5.80***
CADF	-6.04***	-5.67***

Note: Rows LLC, IPS, and CADF report the LLC, IPS, and CADF panel unit root tests. Single(*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels,respectively. The null hypothesis of a unit root is rejected if the test statistic is significant.

المنارة للاستشارات
www.manaraa.com

Table 4.4 Fixed Effects Model Extimates on Crack Ratio and Crack Spread

	Crack Ratio		3-2-1 Crack Spread	
	Estimate	Robust Std. Err.	Estimate	Robust Std. Err.
Oil stock	3.55e-06**	1.65e-06	.000083***	.000015
Gasoline stock	3.36e-06	3.87e-06	-.000014	.000042
EDC	2.67e-09	3.54e-09	4.64e-08	5.25e-08
Ethanol production	-.000031***	3.77e-06	-.00025***	.000061
Supply disruption	.12***	.037	.79	.64
Gasoline import	-.000016**	7.10e-06	-.00040***	.000061
HHI	.00018**	.000084	.0024**	.0010
January	.00090	.011	-.24	.19
February	.0017	.013	.36	.22
March	.091***	.015	1.91***	.26
April	.16***	.020	3.32***	.34
May	.19***	.022	3.51***	.43
June	.15***	.019	2.91***	.39
July	.10***	.017	2.22***	.29
August	.10***	.018	2.67***	.28
September	.071***	.018	2.66***	.36
October	.034*	.018	2.02***	.35
November	.014	.014	.63	.22
R^2	0.4349		0.3643	

Note: The STATA *xtivreg2* command with the robust and *bw* options is used. Single (*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

المنارة للاستشارات
www.manaraa.com

Table 4.5 Panel SUR Estimates on Crack Ratio and Crack Spread

	Crack Ratio		3-2-1 Crack Spread	
	Estimate	Std. Err.	Estimate	Std. Err.
Oil stock	4.73e-07**	2.42e-07	6.86e-06	4.32e-06
Gasoline stock	4.02e-07	4.41e-07	-1.58e-06	9.17e-06
EDC	5.79e-09***	1.25e-09	1.13e-07***	1.84e-08
Ethanol production	-.000026***	4.16e-06	-.00019***	.000062
Supply disruption	.17***	.041	2.27***	.77
Gasoline import	-3.51e-06***	8.71e-07	-.000078***	.000019
HHI	.000015	.000029	.00025	.00051
January	.023	.015	.10	.29
February	.012	.019	.34	.36
March	.067***	.021	1.40***	.39
April	.12***	.023	2.44***	.42
May	.13***	.023	2.67***	.43
June	.095***	.023	2.26***	.43
July	.071***	.023	1.63***	.43
August	.059***	.022	1.67***	.42
September	.023	.021	1.46***	.40
October	.0040	.019	1.10***	.37
November	.00091	.015	.34	.29

Note: Single (*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

المنارة للاستشارات
www.manaraa.com

Table 4.6 Regression Results on Crack Ratio with Individual PADD Data

	PADD I	PADD II	PADD III	PADD IV	PADD V
Oil stock	.000026	.000020***	9.38e-06***	-.000033	-8.64e-06
Gasoline stock	.000024***	.000013	.000024**	-.00014*	.000017
Distillation cap.	.00094*	.0015	7.5e-08	-.0077***	-.0042***
Ethanol prod.	-.000052***	-0.000063***	-.000045**	-.000016***	-.000055**
Supply disrup.	.68***	-0.26	.66**	.56*	.08
Gasoline import	-.000066***	.0035**	-.000099	-.013	.00049***
HHI	-.00028	-.00074	-.0028**	.0012	.001
January	-.034	.024	-.029	.055	-.067
February	-.066	.056	-.034	.079	-.072
March	.029	-.06	-.037	.18*	-.12
April	.056	-.084	-.029	.28**	-.075
May	.016	-.19	-.022	.18	-.15
June	-.013	.019	-.027	.12	-.0027
July	.0043	-.059	-.046	.12	-.11
August	.0019	-.096	-.038	.14	-.24
September	-.069	-.0099	-.095	.13	-.18
October	.014	-.031	-.058	.26**	.0058
November	-.041	-.049	-.081*	.11*	-.062
Constant	-1.09	-6.61*	-.012	-.31	13.23***
R^2	.7251	.6148	.8309	.7293	.6070

Note: The STATA *ivreg2* command with *bw* option is used. Single (*), double (*), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

المنارة للاستشارات
www.manaraa.com

Table 4.7 Basic Market Parameters

Paremeters	U.S. corn market	U.S. gasoline market	U.S. ethanol market
Price elasticity in demand	-0.15	-0.35	–
Price elasticity in supply	0.27	0.25	–
Average price in 2007	\$3.40/bu.	\$2.84/gal.	\$2.01/gal.
Total production in 2007	13.07 billion bu.	142 billion gal.	6.4 billion gal.
Change in price	\$1.27/bu.	\$0.23/gal.	\$0.27/gal.
Income elasticity of demand	0.1	0.4	–
Disposable personal income in 2007 (billion dollars)	10,170.41		

Table 4.8 Welfare Changes of Corn, Ethanol, Gasoline/Fuel Markets, 2007

Corn market (billion dollars)	
Change in consumer surplus (CS)	-16.17
Compensating variation (CV)	-16.17
Change in producer surplus (PS)	14.05
Change in CS & PS	-2.12
Change in CV & PS	-2.12
Reduced LDPs	3.45
Gasoline market (billion dollars)	
Change in CS	32.20
Change in CV	32.18
Change in PS	-31.40
Change in CS & PS	0.79
Change in CV & PS	0.77
Ethanol market	
Change in PS (billion dollars)	0.86
Volumetric excise tax credit in U.S. (dollars per gallon)	0.51
U.S. taxpayer cost of tax credit (billion dollars)	3.26
Net welfare loss (billion dollars)	
(based on CS)	0.28
(based on CV)	0.30

المنارة للاستشارات
www.manaraa.com

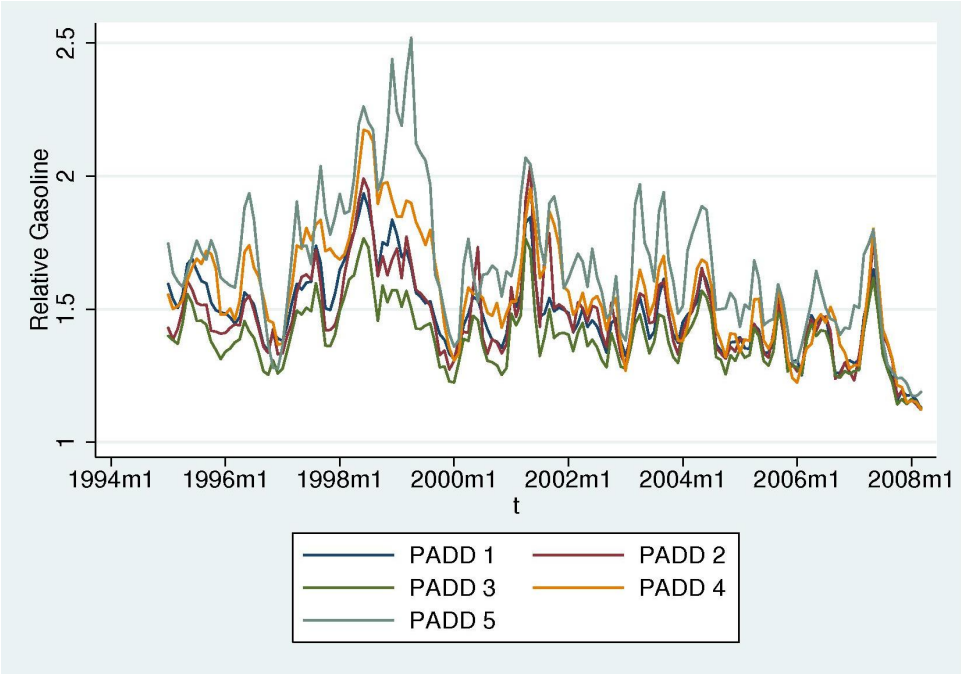


Figure 4.1 Crack Ratio, Jan. 1995 - Mar. 2008

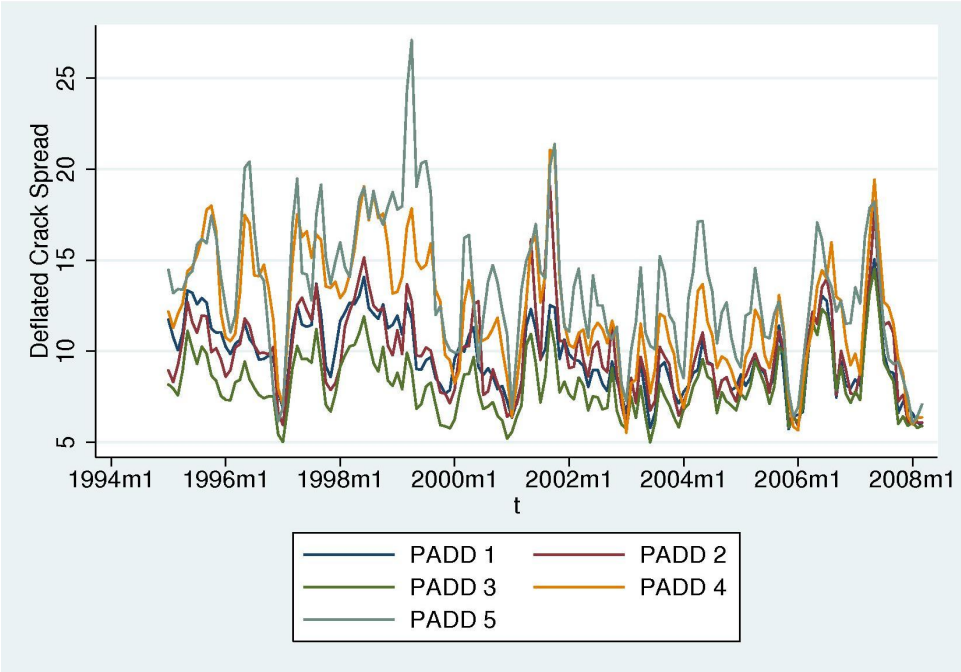


Figure 4.2 Deflated 3:2:1 Crack Spread, Jan. 1995 - Mar. 2008

المنارة للاستشارات
www.manaraa.com

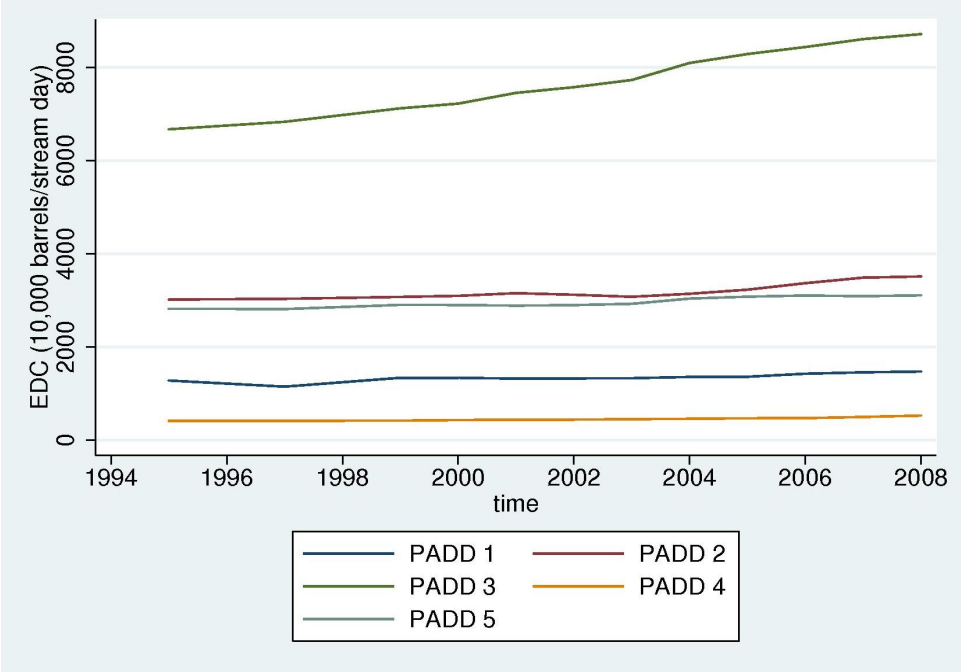


Figure 4.3 Annual Equivalent Distillation Capacity (10,000 barrels/steam day)

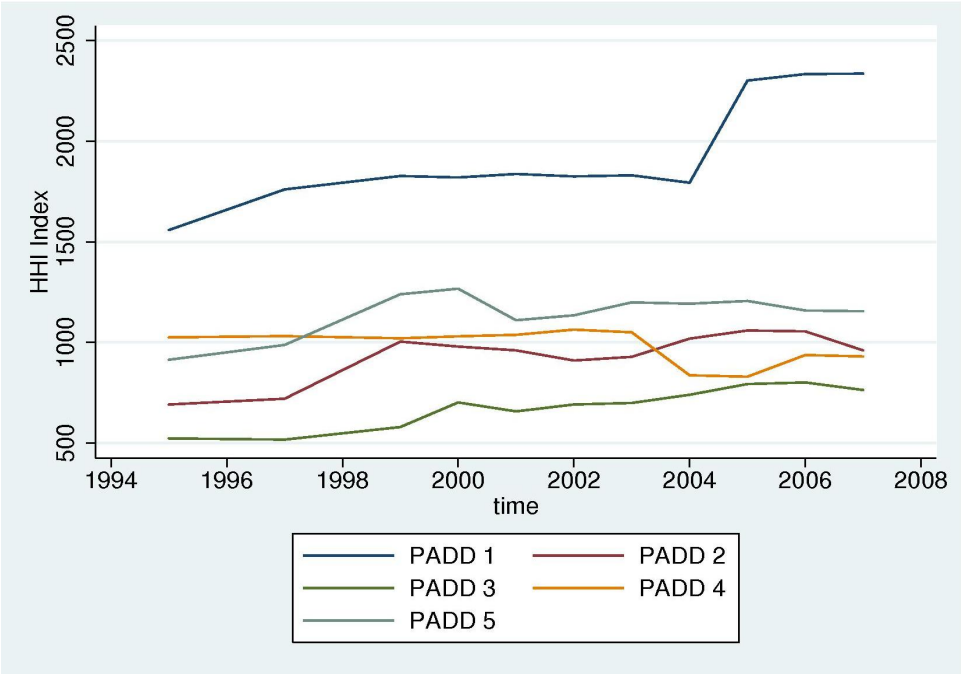


Figure 4.4 Annual HHI, 1995-2007

المنارة للاستشارات
www.manaraa.com

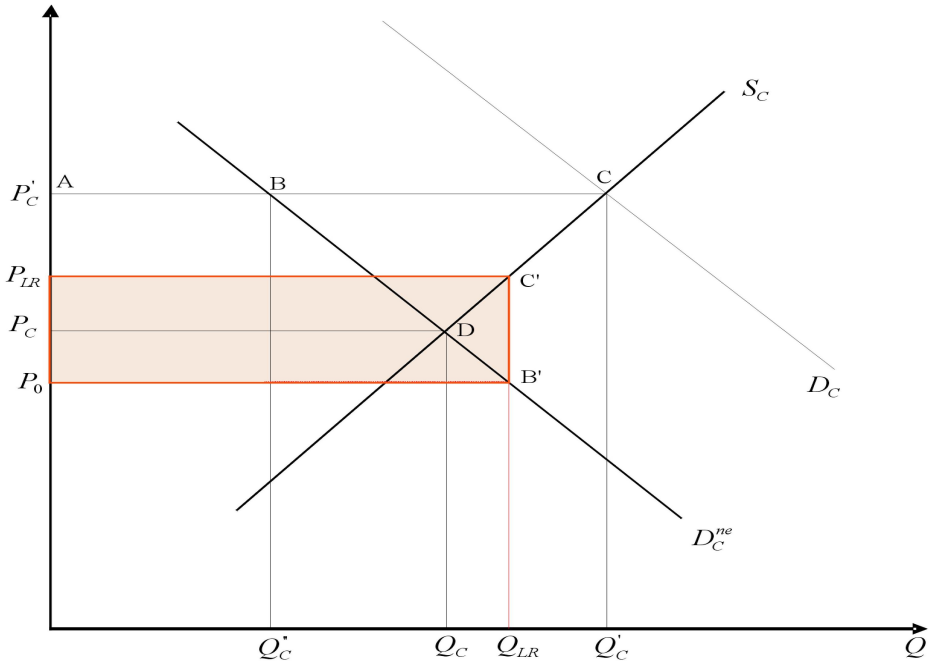


Figure 4.5 Corn Market

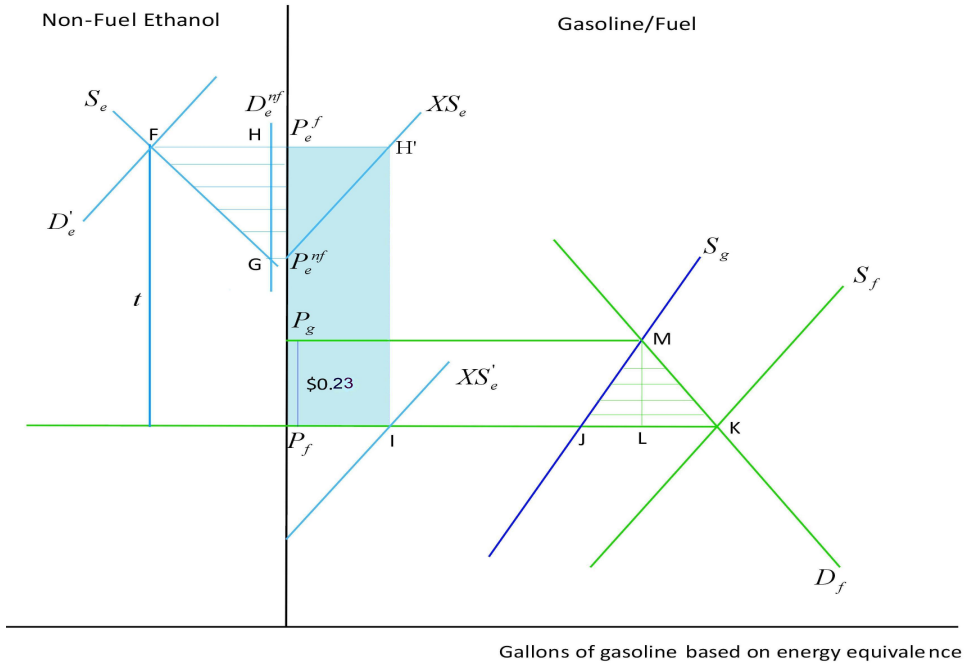


Figure 4.6 Ethanol, Gasoline, and Transportation Fuel Markets

المنارة للاستشارات
www.manaraa.com