THREE ESSAYS ON THE ECONOMIC VALUE OF INNOVATION AND QUALITY WITHIN THE SOYBEAN SUPPLY CHAIN

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by

JEWELWAYNE S. CAIN

Dr. Joe L. Parcell, Dissertation Supervisor

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

THREE ESSAYS ON THE ECONOMIC VALUE OF INNOVATION AND QUALITY WITHIN THE SOYBEAN SUPPLY CHAIN

presented by Jewelwayne S. Cain,

a candidate for the degree of doctor of philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

Professor Joe L. Parcell

Professor Patrick Westhoff

Professor Raymond E. Massey

Professor Felix B. Fritschi

DEDICATION

… To Ellen, my life.

… To Miel, my future.

… To Papa and Mama, my foundation.

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"There is nothing outside of yourself that can ever enable you to get better, stronger, richer, quicker, or smarter. Everything is within. Everything exists. Seek nothing outside of yourself."

- Miyamoto Musashi

My utmost gratitude goes to two great mentors who have inspired and motivated me to earn my Ph.D. In so many ways and so many times, their main message to me is embodied in the samurai quote above.

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THREE ESSAYS ON THE ECONOMIC VALUE OF INNOVATION AND QUALITY WITHIN THE SOYBEAN SUPPLY CHAIN

Jewelwayne S. Cain

Dr. Joe L. Parcell, Dissertation Supervisor

ABSTRACT

Population growth and rise in personal income worldwide have led to a high rate of increase in global food demand. A decreasing number of agriculture workers across the globe and slowing expansion of agricultural acreage make agricultural innovation crucial to increasing agricultural productivity. One of the most important global agricultural crops is soybeans. So far, innovations in the seed quality of soybean has enabled farmers to meet growing global food and energy demands—particularly on specific nutrient components such as protein and oil—and to mitigate the effects of several biotic and abiotic stresses facing soybean plants. However, the farmer's ability to remain competitive and meet demand through innovation still requires further understanding of several areas, three of which are the focus of this study. This dissertation consists of three chapters, with each chapter containing an essay addressing a specific topic while following a general theme--which is analyzing the economic value of innovation and quality within the soybean supply chain. The first chapter looks at the evolution of soybean drought-tolerance to consider if the impact of innovation is evenly distributed geographically in three U.S. relative soybean maturity zones. Results show that crops planted in all three relative maturity zones are exhibiting increasing tolerance over time and only against droughts occurring between August and October. There is evidence, however, that soybeans planted in relative maturity zone 4 exhibited the largest improvement in drought tolerance, while those planted in relative maturity zone 3 exhibited the least. In the second chapter, a two-stage hedonic model is presented to estimate marginal implicit values of two important soybean traits—protein and oil content—and analyze the demand and supply factors that affect these values. The results show significant and positive marginal implicit values, suggesting that there is an incentive for U.S. farmers to produce soybeans with higher quantities of protein and oil content. Finally, the third chapter considers a market share model using import quantity and unit-value data of four soybean exporters to the Philippines—U.S., Canada, China, and the rest of the world (ROW)— to determine whether the downward trend in the U.S. market share is due to inherent soybean quality differences or relative price changes. Results show that the Philippine demand for imported soybeans is less responsive to relative price changes and is more determined by quality differences, which indicates that the decline in the U.S. import market share is due to preferences shifting toward soybean qualities inherent in non-U.S. soybeans.

CHAPTER 1. GENERAL INTRODUCTION

1.1. Introduction

Global population growth, climate change, droughts, flooding, and diseased crops along with world-wide disruptions that have forced thousands of people to leave their homes with virtually nothing have led to tremendous increases in global food demand. Yet, despite the decreasing number of agriculture workers and a slowdown in agricultural expansion as farmers hold off on investment in favor of saving anticipating more natural disasters, food production continues to meet global demand. The stability in both national and global food supplies have been due to improvements in productivity brought about by agricultural innovation. Innovations in the quality of seeds, which are one of the essential inputs in production, are accomplished through plant breeding, seed production, seed marketing, and applied genetics by farmers, extension offices, and private companies. Fernandez-Cornejo (2004), Fernandez-Cornejo and Schimmelpfennig (2004), Steigert et al. (2010), Heisey and Fuglie (2011), Fuglie and Toole (2014), and Heinemann et al. (2014) provide excellent overviews of the evolution of seed innovation in the U.S.

One of the most important global agricultural crops is soybeans. Innovations in the quality of soybean seeds have increased soybean production and yields worldwide. Not only have seed innovations enabled farmers to meet growing global food demand, but it is also providing biofuel for new types of energy demands. Farmers have been enabled to mitigate effects from several biotic and abiotic stresses facing soybean plants. For instance, herbicide- and insect-resistant varieties have already been distributed to the market (Fernandez-Cornejo, 2004). Another global trend that has benefited from agricultural innovation is the increase in economic importance of protein and oil content in soybeans. For instance, feed manufacturers have become more discerning of the nutrient factors in their products, such as protein found in soybean meal. Likewise, rising demand for edible oil relative to the soybean supply has significantly increased oil value, underscoring the market potential of increasing oil content in soybeans.

This dissertation consists of three distinct essays addressing a specific topic while following a general theme, which analyzes the economic value of innovation and quality within the soybean supply chain.

1.2. Organization of the Dissertation

This dissertation is organized into four chapters. The current chapter presents a general introduction to the chapters that follow and provides an outline for the organization of the dissertation.

Chapter 2 looks at drought-tolerance of U.S. soybean crops to examine if technology innovation in soybean seeds are evenly-distributed geographically. Drought is one of the major environmental challenges faced by farmers. A major consequence of drought is diminished crop growth or yield. One solution that would address problems relating to drought is innovation in seed quality through plant breeding, seed production, seed marketing, and applied genetics by farmers, extension offices, and private companies. Given that agricultural crops are location-specific and geographically-dispersed, it is expected that research and development (R&D) efforts will not be centralized. As such, we should find innovation to be different spatially. In addition, economic incentives drive innovation. Seed innovators, given that they are primarily profit-driven, will invest more of their R&D on seeds that yield the most potential. I tested this hypothesis by analyzing drought-tolerance of soybean crops in counties belonging to three soybean maturity zones over time. The maturity environment strongly influences how climatic conditions affect plant development. It is expected that there will be differences in drought-tolerance of soybean crops across maturity areas due to innovators investing more R&D in the maturity zone that yields the highest potential. Lower numbered maturity groups, i.e., relative maturity groups 1 through 3, cover more acres, accounting for about 70 percent of US soybean production; therefore, greater public and private investment is funneled into these types of soybean varieties. Given this, it should be expected that soybean crops from the lower numbered maturity groups have become more drought-tolerant over time. By comparing soybean maturity zones in the U.S. Midwest, I am able to assess whether one important production trait, drought tolerance, has been given equal scientific attention between different growing regions of different production importance considering that there is a potential for soybeans planted in lower-numbered relative maturity zones. Results show that crops planted in all three relative maturity zones are exhibiting increasing tolerance over time and only against droughts occurring between August and October. There is evidence, however, that soybeans planted in relative maturity zone 4 exhibited the largest improvement in drought tolerance, while those planted in relative maturity zone 3 exhibited the least.

In Chapter 3, a two-stage hedonic model is presented to estimate marginal implicit values of two important soybean traits—protein and oil content—and analyze demand and supply factors that affect these values. Soybean quality is becoming more important as markets realize its impact in relation to utility. For instance, levels of soybean protein and oil content impact animal feed efficiency and the amount of oil to be used for food, fuel, or industrial purposes. To respond efficiently to pricing signals in producing soybeans with specific quality attributes desired by consumers, producers need to understand how the implicit values of these quality attributes—protein and oil—are determined, which ultimately affects the final price of soybeans. This is especially important considering the investments being made in seed innovation to develop or improve varieties of soybeans that contain levels of quality attributes desired by both consumers and producers. Using a hedonic price model in the first stage, I estimated the marginal implicit values of soybean protein and oil. In the second stage, I used a structural attributes model to analyze the demand and supply factors that affect these values in order to examine soybean quality-price relationships. I include cross-state effects to analyze how protein and oil content in soybeans produced in other states affect the price of soybeans as well as implicit values of these two soybean quality attributes. The results show significant and positive marginal implicit values, suggesting that there is an incentive for U.S. farmers to produce soybeans with higher quantities of protein and oil content.

Chapter 4 looks at soybean quality in general to analyze the recent downward trend in the U.S. market share of soybean imports in the Philippines. Competitiveness in the international soybean trade market is driven not only by soybean price, but also by quality. The relative importance of these two factors are likewise dependent on the nature of the market. If the market is dominated by buyers who consider soybeans as highly homogenous, then the market will be highly sensitive to relative price changes. On the other hand, if the market represents the current global trend, buyers who place increasing importance on the quality of soybeans, the market will be less sensitive to relative price changes. Because import quality is unknown, I use a market share model using import quantity and price data from four of the Philippine soybean import sources—United States, Canada, China, and the Rest of the World (ROW)— to determine whether the downward trend in U.S. market share is due to inherent soybean quality differences or relative price changes. Results of the model are further used to estimate market share trends, preference parameters, and price elasticities to help identify relative preference of the Philippine market for U.S. soybeans compared to soybeans from Canada, China, and ROW. Results show that the Philippine demand for imported soybeans is less responsive to relative price changes and is more determined by quality differences, which indicates that the decline in the U.S. import market share is due to preferences shifting toward soybean qualities inherent in non-U.S. soybeans.

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CHAPTER 2. IS TECHNOLOGY INNOVATION IN SOYBEAN DEVELOPMENT EVENLY DISTRIBUTED GEOGRAPHICALLY?

2.1. Introduction

Global population growth and increases in personal incomes worldwide have led to high rate of increases in global food demand (Rosegrant and Cline, 2003). At the same time, the share of global population working in farms has declined and the expansion of land for planting crops has not kept pace with rising global demand (Miller et al., 2010; Write, 2012). Yet despite these trends, agricultural production continues to meet global demand due to improvements in productivity. Such productivity increases are made possible primarily by continuous process of agricultural innovation (Fogel, 2004; Fuglie and Toole, 2014; Tolhurst and Ker, 2015). Innovation in seeds, one of the essential inputs in agricultural production, is done through plant breeding, seed production, seed marketing, and applied genetics by farmers, extension offices, and private companies.[1]

One of the most important global agricultural crops is soybeans. Soybean crops are an important source of oil and protein. Innovations in the quality of soybean seeds has increased soybean production and yield worldwide (Ainsworth et al., 2012). Not only have seed innovation enabled farmers to meet growing global food and energy demand, it has also enabled farmers to mitigate effects of several biotic and abiotic stresses facing soybean plants. One common source of stress is prolonged periods of drought. Drought is a situation where either there is less than average precipitation in the air or there is less

[1] Fernandez-Cornejo (2004), Fernandez-Cornejo and Schimmelpfennig (2004), Steigert et al. (2010), Heisey and Fuglie (2011), Fuglie and Toole (2014), and Heinemann et al. (2014) provide excellent overviews of the evolution of seed innovation in the U.S.

amount of moisture in the soil. Left unaddressed, a major consequence of drought is diminished crop growth and yield production.

The U.S. has experienced several major periods of drought since the early 1900s. The worst one was during the summer of 1988 when 35 states were affected and rainfall totals were up to 85% below normal. The catastrophic results were low crop production and livestock deaths. Thus, drought poses a significant threat to meeting the rising global food demand, providing a strong incentive for seed producers to develop more drought-tolerant soybeans (Singh et al., 2012).

While correct farm management practices that minimize the environmental stress due to drought are constantly being advocated and adopted (McWilliams et al., 1999), increasing focus is being given to creating and developing soybean varieties that are more drought-tolerant through seed innovation. Plant breeding programs have offered better alternatives to appropriate farm management practices. Since the start of the 20th century, plant breeding activities by both public and private entities have generated varieties with improved drought tolerance. The latest research and development (R&D) efforts are now focused on understanding plant response to water deficit at the genetic and molecular level. Despite significant progress in seed innovation, there is still a large gap between crop yields under optimal conditions and crop yields under drought conditions (Cattivelli et al., 2008).

Given that agricultural production is location-specific and are geographically-dispersed, it is expected that research and development (R&D) efforts will not be centralized (Write, 2012). As such, innovation should be different spatially. In addition, economic incentives drive innovation. Since the seminal works of Zvi Griliches on the economics of technical change (Griliches 1957, 1958, 1960), many studies have analyzed the significant role of economic incentives in determining how benefits from new technologies are distributed (Tokgoz, 2006; Desmet and Rossi-Hansberg, 2012; Hurley et al., 2014). Heckman (2005) discussed how Griliches' work on hybrid corn has laid the foundation for these studies:

> [Griliches'] work showed that economic logic can be used to empirically quantify the impacts of the incentives which determine the distribution of benefits from research activity and, by implication, the social and private returns from investing in that research. His papers demonstrated how the diffusion of hybrid corn was related to the profitability from employing it, and how the benefits from the research investments in different hybrids varied with the extent of their markets and the cost conditions at the time of their development which in turn depended on prior development of hybridization techniques (pp. 6-7).

Seed innovators, given that they are primarily profit-driven, will invest more of their R&D expenditures on seeds that yield the most profit potential. Griliches (1960) used the same principle in explaining the geographic differences in the development of seed varieties: A superior variety will be developed (with contributions from experimental stations) and will become available in an area if seed producers expect it to be profitable. Profits in turn will depend on the size of the seed market as well as the costs of market entry in that area. Griliches (1960) added that profitability for seed producers will also depend on the rate of adoption by farmers. Adoption rate in turn will depend on the profitability that farmers expect when using these new seed varieties.[2]

[2] While adoption of new technology is a significant determinant of technology innovation, this chapter will not explore the economics of technology adoption and instead focuses only on technology innovation. For recent reviews of the literature on technology adoption, see Barham et al. (2015) and Sriwannawit and Sandstrom (2015).

I test this hypothesis by analyzing drought-tolerance over time of soybean crops in 101 U.S. counties belonging to three soybean maturity zones (zones 3, 4 and 5). The maturity environment strongly influences how climatic conditions affect plant development. Soybean quality attributes vary from north to south due to climate, which in turn affects variation in soybean germplasm seeds. For the production of soybeans in North America, 13 growing regions are differentiated as relative maturity zones Soybean genetics, therefore, differ across these relative maturity zones (Naeve et al., various years). Lower numbered groups adapt more to northern climatic regions and the designated number increases as you move south.

It is expected that there will be differences in drought-tolerance of soybean crops across maturity zones due to innovators investing more R&D in the maturity zone that yields the highest potential soybean sales. Lower numbered maturity groups cover more acres and account for about 70 percent of soybean production. Because of the larger market, it can be expected that there is a tendency for greater public and private investment into the types of soybean varieties that are planted in lower numbered maturity groups. Given this, it should be expected that soybean crops from the lower numbered maturity groups to have become more drought-tolerant over time. On the other hand, areas outside of the lower-numbered maturity group regions are more susceptible to drought because of poorer soil type, seasonal rain patterns, and a hotter climate. By comparing the three soybean maturity zones, I am able to assess whether one important production trait, drought tolerance, has been given equal scientific attention among different growing regions of different production importance considering that in the point of view of U.S. seed producers, there is potential for higher returns with seeds from lower-numbered relative maturity zones.

2.2. Empirical Model

The literature is rich in studies that analyze the effects of extreme weather conditions on crop levels and variability in the U.S. Most of these studies are on agronomic crops, especially corn. Among the widely used types of analysis are field experiments (Singh et al., 2012), simulation techniques (Terjung et al., 1984; Mearns et al., 1996; Eitzinger et al., 2003) and regression techniques (Thompson, 1986; Mendelsohn et al., 1994; Isik and Devadoss, 2006; Lobell et al., 2007; Almaraz et al., 2008; Sarker et al., 2012; Du et al., 2015).[3] Regression-based studies that look at the effects of weather on soybean crops, in particular, include Chen et al. (2004), Prasad et al. (2006), Deschênes and Greenstone (2007), McCarl et al. (2008), Schlenker and Roberts (2009), Roberts and Schlenker (2010), and Yu and Babcock (2010). While several of these studies cover multiple U.S. states, none of them analyzed data across relative maturity zones. Drought conditions affect soybean plants differently at different growth stages. For instance, Eck et al. (1987) found that water deficit stress during the full pod stage lead to greater reduction in soybean yield than stress between flowering and beginning of pod development stages.[4] It is for this basis that this chapter considers the effects of drought in three separate durations: early to middle vegetative stage of soybean (April to June); late vegetative to

[3] See also McKeown et al. (2006), Schlenker and Roberts (2009), and Roberts and Schlenker (2010) for excellent reviews of methods.
[4] Fehr et al. (1971) describes soybean growth as encompassing the vegetative stages (emergence, unrolled unifoliate leaves, first unrolled trifoliate leaf, second unrolled trifoliate leaf, and successive unrolled trifoliate leaf afterwards) and the reproductive stages (beginning bloom, full bloom, beginning pod development, full pod, beginning seed, full seed, beginning maturity, and full maturity).

early reproductive stage (June to August); and, middle to late reproductive stage (August to October). This is in contrast to studies mentioned above where only one aggregate drought measure was used for each year.[5]

To analyze drought tolerance of soybean crops from the three soybean maturity zones over time, I used a modified version of the yield-drought model of Yu and Babcock (2010), which is a multivariate panel data regression model:

$$Y_{i,t} = \alpha_i + \sum_{m=1}^{3} \beta_{1,m}(M \times T) + \sum_{m=1}^{3} \beta_{2,m}\left(M \times DI_{i,t}\right) + \sum_{m=1}^{3} \beta_{3,m}\left(M \times DI_{i,t} \times T\right) + \sum_{m=1}^{3} \beta_{4,m}\left(M \times DI_{i,t}^{2}\right) \tag{2.1}$$

where subscripts *t*, *i*, and *m* denote time, county, and maturity zone, respectively; *Y* denotes soybean yield in natural log form; *T* is a time trend variable with a starting value of 1 for year 1974 and 40 for year 2013; and *M* is the soybean maturity zone dummy variable. *DI* is a drought index, which I also adopted from Yu and Babcock (2010). The Yu-Babcock drought index is a composite measure that has the advantage of capturing not only hot conditions, but dry conditions as well:

$$DI_{i,t} = \left[-max\left(0, CLDD_{i,t}^{stand}\right)\right] \times \left[min\left(0, TPCP_{i,t}^{stand}\right)\right] \tag{2.2}$$

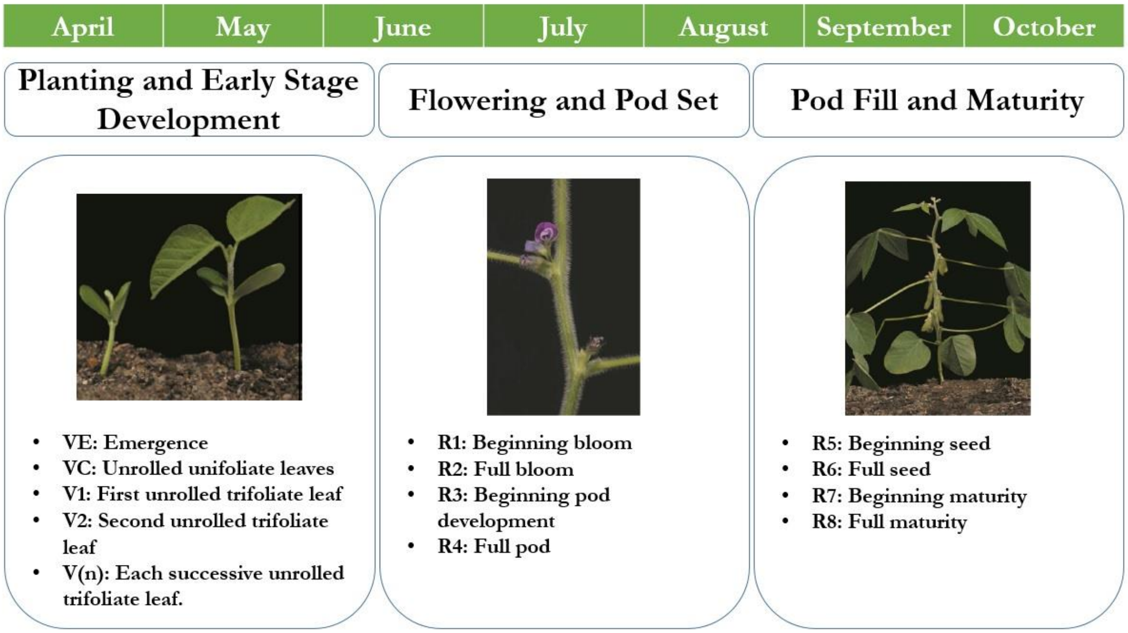
[5] For instance, Chen et al. (2004) aggregated weather data from April to November; Prasad et al. (2006) aggregated weather data from June to September; and, Yu and Babcock (2010) aggregated weather data from June to August. The last two consider only the effect of drought during the reproductive stages of soybean growth.

CLDD denotes cooling degree days while *TPCP* stands for total monthly precipitation. *CLDD* is the number of degrees above 65° Fahrenheit and is, thus, a measure of heat. The term is based on the idea that at high temperatures, energy demand for air conditioning increases. Both are standardized by subtracting county averages (across years) from each observation and then dividing the result by the county-level standard deviations (also across years). Higher values of the index mean either the temperature measure is above average, the rainfall measure is below average, or both—indicating more adverse drought conditions.

To capture the possibility that droughts occurring at different parts of the year affect yield differently, I ran three estimations, each using one of the three alternative measures of the drought index: one measuring droughts occurring between April to June; another for droughts occurring between June to August; and a third for droughts occurring between August and October. These three alternative measures of the drought index approximately correspond to the three periods in the life cycle of soybeans (see Figure 2.1).

Soybeans are planted as early as April and they are harvested around October. The drought indices are calculated by aggregating *CLDD* and *TPCP* over each of these periods and over each relative maturity zone. In total, there are six measures of drought indices used in this chapter. The quadratic form of drought index is added to capture the possibility that the rate of marginal effect of drought on yield could be increasing or decreasing.

Figure 2.1. Growing Season of Soybean and the Corresponding Biological Stages



Note: V stands for a Vegetative Stage, while R stands for a Reproductive Stage (Iowa State University Extension, PM1945)
Source: Iowa State University Soybean Extension and Research Program (1945), "Soybean Growth and Development"
http://extension.agron.iastate.edu/soybean/production_growthstages.html (Accessed: April 14, 2015).

Equation 2.1 consists of a deterministic trend yield, $\alpha_i + \sum \beta_1(M \times T)$, the drought-driven deviations from the trend, $\sum \beta_2(M \times DI) + \sum \beta_3(M \times DI \times T) + \sum \beta_4(M \times DI^2)$, and the residual, $\epsilon_{i,t}$. The deterministic trend yield contains a time-invariant county-specific intercept term, α_i, that will also serves to capture heterogeneity across panels such as soil type and quality (Schlenker and Roberts, 2009). The second term of the deterministic trend yield is the slope specific to each relative maturity zone: I assume in this study that the yield over time is generally similar among counties located in the same relative maturity zone. This chapter focuses primarily on the drought-driven deviations. I assume that the deviations are also specific to each relative maturity zone: soybean yield from counties belonging to the same relative maturity zone experience the same effect of drought. Differentiating Equation 2.1 with respect to the drought index for a particular relative maturity zone m, will show the marginal effect of drought on soybean yield:

$$(2.3) \quad \frac{\partial Y_{i,t}}{\partial DI} = \beta_{2,m} + \beta_{3,m}T + 2\beta_{4,m}DI_{i,t}$$

Since it is given that the consequence of drought is diminished yield production, the marginal effect as defined above is expected to be negative ($\partial Y_{i,t}/\partial DI < 0$). Further differentiating Equation 2.3 with respect to time trend, T, will capture the change in the effects of drought on yield over time for relative maturity zone m:

$$(2.4) \quad \frac{\partial Y_{i,t}}{\partial DI \partial T} = \beta_{3,m} \begin{cases} > 0 \; more\ drought - tolerant\ over\ time \\ < 0 \; less\ drought - tolerant\ over\ time \end{cases}$$

If $\partial Y_{i,t}/\partial DI \partial T$ is positive, this means that soybean crops of this relative maturity zone are generally becoming more drought-tolerant over time. If the marginal effect over time is negative instead, then the soybeans are becoming less drought-tolerant over time.

2.3. Data

Data on soybean yield were obtained from the website of the National Agricultural Statistics Service of the U.S. Department of Agriculture, while matching data on *CLDD* and *TPCP* were obtained from the website of the National Climatic Data Center of the National Oceanic and Atmospheric Administration. Table 2.1 presents the list of 101 counties. The counties are grouped by state (rows) and by relative soybean maturity zone (columns).

Table 2.1. List of Counties by State and Relative Soybean Maturity Zone, 1974 To 2013 (Number of Counties in Parenthesis)

State	Maturity zone 3 (45)		Maturity zone 4 (28)		Maturity zone 5 (28)	
Arkansas (9)					Arkansas Ashley Chicot Desha Independence	Jackson Lonoke Mississippi White
Illinois (19)	Adams Champaign Hancock Henry Kankakee LaSalle	McLean Morgan Peoria Sangamon Vermillion Warren	Christian Coles Macoupin Marion	Shelby St. Clair Washington		
Indiana (9)	Allen Boone Clinton Fulton	Jasper Randolph Tippecanoe	Bartholomew	Vanderburgh		
Iowa (7)	Appanoose Davis Des Moines Henry	Jefferson Page Ringgold				
Kansas (15)	Jewell		Clay Cloud Dickinson Douglas Franklin Jefferson	Marion McPherson Mitchell Osage Shawnee	Kingman Sedgwick	LaBette
Kentucky (3)			Boone	Fayette	Edmonson	
Missouri (16)	Audrain Caldwell Chariton	Lewis Nodaway Ralls	Boone Miller Moniteau	Pettis Saline St. Louis	Butler Dade	Dunklin Jasper
Nebraska (12)	Butler Douglas Fillmore Furnas Hall Kearney	Lancaster Nuckolls Phelps Polk Saunders Seward				
Oklahoma (2)					Kay	Muskogee
Tennessee (9)					Cannon Carroll Hardeman Macon Maury	Obion Rutherford Tipton Weakley

Notes: Number of counties: 101; number of years: 40 (1974 to 2013); total number of observations: 4,040.

Figure 2.2. Map of Counties Used in the Study, Distributed Across Relative Soybean Maturity Zone 3 (blue), 4 (green), and 5 (red)

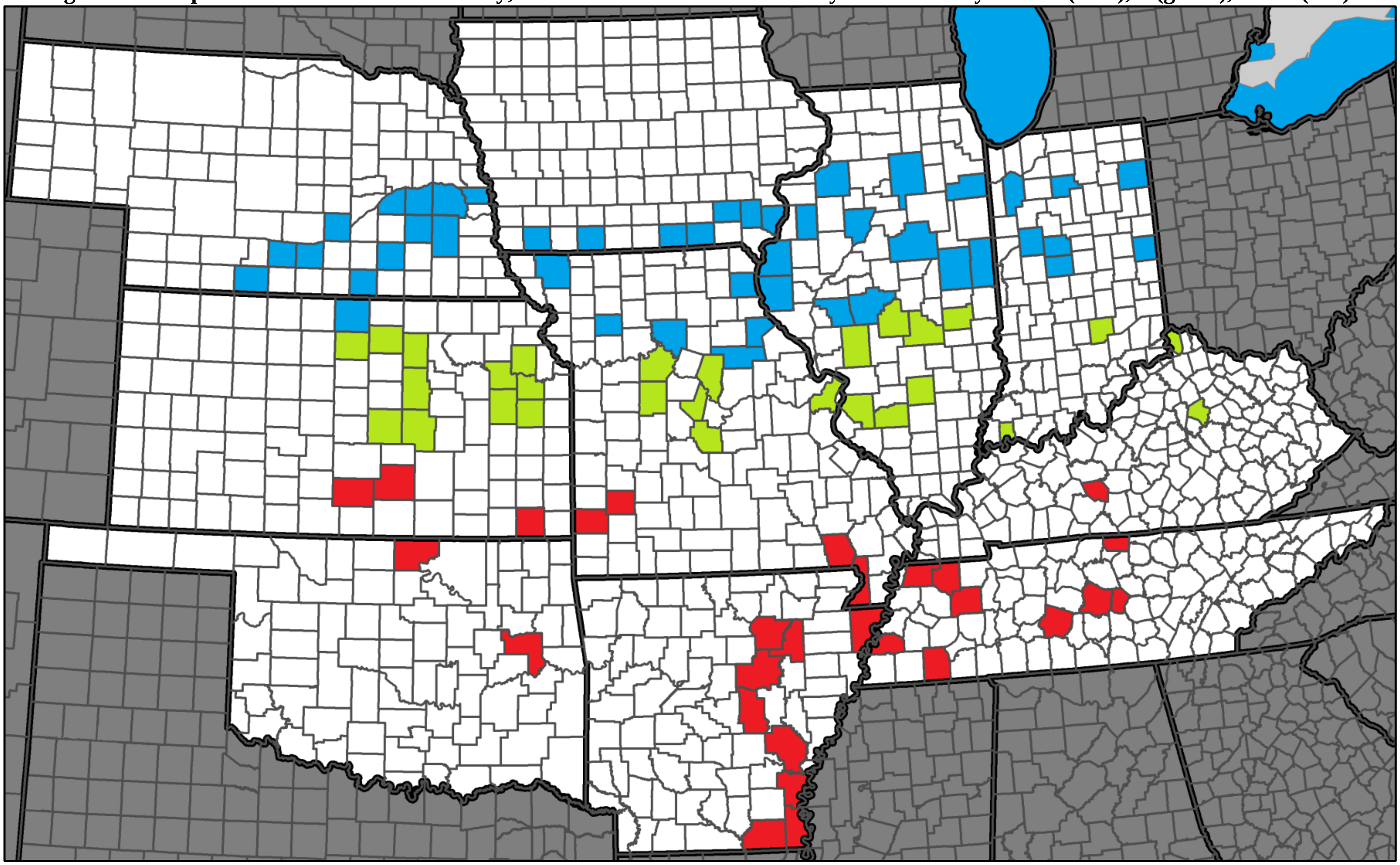


Figure 2.2 shows a map of counties included in this chapter's analysis.

Counties with incomplete soybean yield data from 1974 to 2013 were dropped from the analysis. Counties with incomplete weather data were also dropped, except in cases where a county has multiple weather stations and missing data from one station can be imputed using available data from another station. Missing data are imputed using a predictive mean matching (PMM) method introduced by Little (1988). The PMM method is a regression-based imputation method and has the advantage of relaxing the normality assumption. Furthermore, the method preserves the distribution of the non-missing values over the missing ones, making it more robust than imputations using the typical linear regression technique.

The imputations are implemented in a Monte Carlo set-up of 1,000 iterations with the final value aggregated as the average of all results.

A summary of descriptive statistics on the variables used in the regression analysis is presented in Table 2.2.

2.4. Estimation

Before identifying the correct regression estimation method to use, I conducted several preliminary tests to check if there was a need to transform the data. I first performed unit root tests on yield and drought data to verify stationarity. Running these tests are also particularly important given that the model uses a time trend variable. Thome (1996) cautioned that there might be some consequences of using a time trend when the series actually do contain unit roots, among which are spurious R-square and biased estimators.[6]

[6] This refers to the so-called situation of "spurious detrending."

Table 2.2. Descriptive statistics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Soybean yield (bushels per acre)					
Maturity Zone 3	1,800	40.2	9.1	11.0	67.7
Maturity Zone 4	1,120	33.2	9.6	8.0	60.5
Maturity Zone 5	1,120	28.6	8.7	7.0	55.3
All maturity zones	4,040	35.0	10.4	7.0	67.7
Drought index (April to June)					
Maturity Zone 3	1,800	0.2563	0.6858	0.0000	6.0982
Maturity Zone 4	1,120	0.2434	0.6245	0.0000	5.9727
Maturity Zone 5	1,120	0.2256	0.5555	0.0000	3.7403
All maturity zones	4,040	0.2442	0.6350	0.0000	6.0982
Drought index (June to August)					
Maturity Zone 3	1,800	0.2403	0.6105	0.0000	5.0263
Maturity Zone 4	1,120	0.2702	0.6145	0.0000	4.8935
Maturity Zone 5	1,120	0.2824	0.6719	0.0000	6.1074
All maturity zones	4,040	0.2603	0.6293	0.0000	6.1074
Drought index (August to October)					
Maturity Zone 3	1,800	0.1911	0.4657	0.0000	7.0365
Maturity Zone 4	1,120	0.1913	0.4954	0.0000	3.7776
Maturity Zone 5	1,120	0.2307	0.5683	0.0000	4.5888
All maturity zones	4,040	0.2022	0.5043	0.0000	7.0365

I employed a Fisher-type Phillips-Perron unit-root test. This test utilizes a meta-analysis that combines the p-values of separate Phillips-Perron unit-root tests applied on each panel (county) to obtain an overall test statistic. To obtain robust results, I used four methods of combining the individual panel test statistics: inverse χ^2, inverse normal, inverse logit, and modified inverse χ^2. Furthermore, in order to minimize complications that would arise due to cross-sectional dependence, a standard procedure of subtracting the cross-sectional averages from each panel data was implemented first before performing the unit-root tests. In each stationary test, I included only one-period county-specific lag based on three information criteria (Akaike, Bayesian, and Hannan-Quinn).

The results are reported in Table 2.3. All tests strongly reject the null hypothesis of the existence of unit roots in all panel data. These results suggest that there is no need to transform the data to address any potential nonstationarity issues in the time series.

The second group of tests involved checking for cross-sectional dependence (contemporaneous correlation of errors across panels), serial correlation, and cross-panel heteroskedasticity. The results of each of these three tests are shown in Table 2.4.

Table 2.3. Fisher-Type Phillips-Perron Unit Root Tests for Panel Data

Variable	Inverse χ^2	Inverse Normal	Inverse Logit	Modified Inverse χ^2
Natural Log of Soybean yield	2437.8932	–43.1657	–66.9305	111.2398
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Drought Index (April to June)	3008.3834	–49.0017	–82.5994	139.6228
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Drought Index (June to August)	2798.5321	–47.3278	–76.8381	129.1823
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Drought Index (August to October)	2630.9304	–45.7954	–72.2361	120.8438
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: The Phillips-Perron test assumes the null hypothesis that all panels are nonstationary versus the alternative hypothesis that at least some of the panels do not contain unit roots. P-values are in parentheses. Each test uses one-period lagged term and assumes the existence of a trend. Finally, to mitigate the impact of cross-sectional dependence, cross-sectional averages are subtracted from each of the four variables.

Significant cross-sectional dependence in errors may cause either inefficient estimators (if the dependence is caused by unobserved common factors not correlated with any of the independent variables) or biased and inconsistent estimators (if such unobserved factors are correlated with the independent variables). Therefore, its existence had to be identified. Using the average R test suggested by Frees (1995, 2004), the resulting test statistic showed that the null hypothesis of no dependence is strongly rejected. This suggests that the cross-sectional units are not independent.[7]

Table 2.4. Analysis of the Error Structure

Test	Drought Index		
	Apr – Jun	Jun – Aug	Aug – Oct
Test for cross-sectional dependence (H_0: No dependence)			
Frees R test	12.861 (0.0000)	7.271 (0.0000)	9.270 (0.0000)
Test for serial correlation (H_o: No serial correlation)			
Wooldridge Wald test	38.706 (0.0000)	12,205 (0.0000)	25.545 (0.0000)
Test for cross-panel heteroskedasticity (H_0: No heteroskedasticity)			
Green modified Wald test	2620.62 (0.0000)	2329.02 (0.0000)	3128.17 (0.0000)

Note: P-values in parenthesis.

Next I tested for serial correlation within each panel using the method suggested by Wooldridge (2002). Drukker (2003) showed that the Wooldridge test is very attractive because it is less restrictive than other tests and it is easy to implement.[8] Results show that there is not enough evidence to reject the null hypothesis of no serial correlation.

For the third test on the error structure, the use of the least squares method on panel data regression requires that variances should not only differ within cross-sectional units, the variances should not differ across units as well (Baum, 2001). I tested for cross-panel heteroskedasticity using a method proposed by Greene (2000). The Greene test calculates a modified Wald test statistic from the residuals of a fixed-effect regression model. The resulting p-values of the modified Wald test statistic indicate that the null

[7] A more common test in the literature is the LM test of Breusch and Pagan (1980). I did not include this test since the Breusch-Pagan test is applicable only for linear specifications.
[8] The Baltagi-Li test, for instance, makes certain specific assumptions about individual effects, whereas the Wooldridge test requires only a few assumptions (see Baltagi and Li, 1995, and Drukker, 2003).

hypothesis of no cross-panel heteroskedasticity is strongly rejected. This means that there is strong evidence the variance differs across panels.

Finally, since the inclusion of states in this analysis is nonrandom and simply due to availability of data, there is a possibility that the estimation results will exhibit selection bias. This is particularly true if the missing data is endogenous. According to Verbeek and Nijman (1992), however, if the selection of observations affects the conditional expectation of each error term in the same way, the bias will not occur. In other words, the bias is absorbed in the fixed effect since it is "fixed" for each county over all periods in the sample. Therefore, using fixed effects panel-data regression would still yield unbiased and consistent estimators.

Based on all these preliminary findings, I ran Equation 2.1 using fixed-effects Prais-Winsten panel-data regression procedure with panel-corrected standard errors. This method takes into account the presence of serial correlation, heteroskedasticity, and cross-sectional dependence. The estimation was done separately for each of the three measures of drought index variables: April to June, June to August, and August to October.

2.5. Results

Table 2.5 shows the results of estimating the effect of drought conditions on annual soybean yield. Columns (3), (4), and (5) correspond to the three model specifications, each one differentiated by the drought index used.

Table 2.5. Estimation Results from Prais-Winsten Regression with Standard Errors Corrected for Autocorrelation, Heteroskedasticity, and Cross-Sectional Dependence Dependent Variable: Natural Log of Soybean Yield

Variable (1)	Parameter (2)	Drought Index Apr – Jun (3)	Drought Index Jun – Aug (4)	Drought Index Aug – Oct (5)
MATURITY ZONE 3				
T	$\beta_{1,m=3}$	0.0191 ***	0.0172 ***	0.0169 ***
$DI_{i,t}$	$\beta_{2,m=3}$	0.0951 *	– 0.1534 ***	– 0.2144 ***
$DI_{i,t} \times T$	$\beta_{3,m=3}$	– 0.0040 **	0.0007	0.0036 *
$DI_{i,t}^2$	$\beta_{4,m=3}$	– 0.0114 *	0.0153 *	0.0235 ***
MATURITY ZONE 4				
T	$\beta_{1,m=4}$	0.0115 ***	0.0107 ***	0.0096 ***
$DI_{i,t}$	$\beta_{2,m=4}$	– 0.0310	– 0.3921 ***	– 0.5353 ***
$DI_{i,t} \times T$	$\beta_{3,m=4}$	– 0.0045	0.0016	0.0120 ***
$DI_{i,t}^2$	$\beta_{4,m=4}$	0.0187	0.0646 ***	0.0161
MATURITY ZONE 5				
T	$\beta_{1,m=5}$	0.0085 ***	0.0077 ***	0.0069 ***
$DI_{i,t}$	$\beta_{2,m=5}$	– 0.1373 *	– 0.2829 ***	– 0.3822 ***
$DI_{i,t} \times T$	$\beta_{3,m=5}$	– 0.0004	0.0012	0.0060 ***
$DI_{i,t}^2$	$\beta_{4,m=5}$	0.0400 **	0.0235 ***	0.0439 ***
Intercept		3.1990 ***	3.2850 ***	3.2646 ***
R-squared		0.9397	0.9541	0.9469

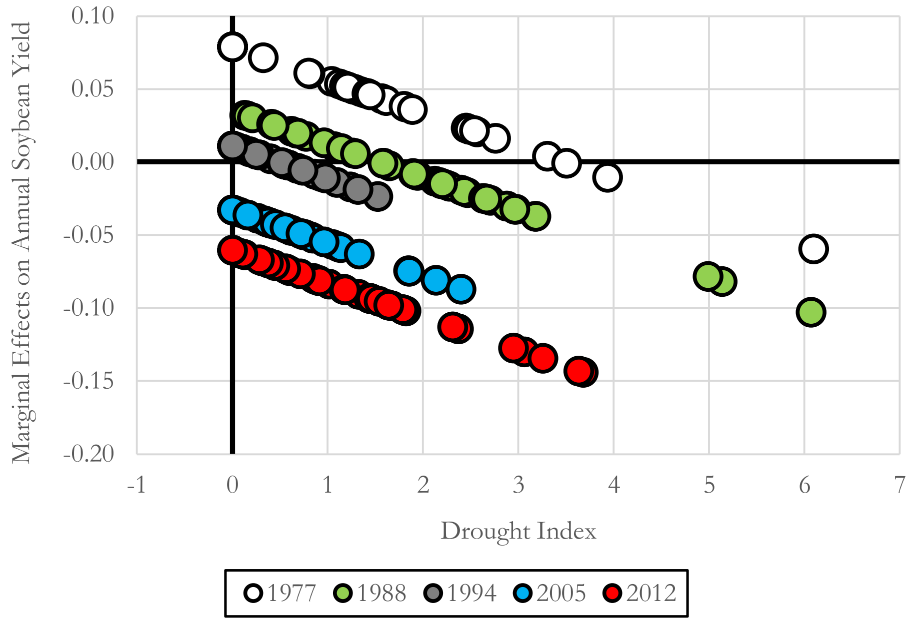
Notes: Number of counties: 101; number of years: 40 (1974 to 2013); total number of observations: 4,040. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

Drought Index for April to June

Column (3) shows the results for April to June drought index, which encompasses the planting and early growing periods of soybeans. The model shows a good fit as indicated by R-squared value of 0.9397.

All coefficients are statistically significant for relative maturity zone 3. Figure 2.3 graphs the marginal effects of the drought index on annual yield of soybeans planted in this zone using the regression coefficients. The years 1977, 1988, 1994, 2005, and 2012 were selected because these years had the most numbers of calculated nonzero marginal effects. These marginal effects are estimated using Equation 2.3.

Figure 2.3. Marginal Effects of April to June Drought Index on Soybean Yield in Maturity Zone 3, Various Years



Two important results can be observed from Figure 2.3. First, higher levels of the drought index were associated with lower soybean yield indicated by the downward-sloping trend in marginal effects across different years. This means that at as drought conditions worsened, yield worsened as well. Second, the effect of drought conditions on soybean yield worsened through time. As shown in the figure, there have been cases when drought conditions actually had a positive effect on yield especially in the earlier years (i.e., marginal effects above zero). However, this has evidently diminished over time (i.e., marginal effects are all negative in 2005 and 2012). This result should be expected given the significant and negative coefficient of the drought-trend interaction term ($\beta_{3,m=3}$) in Table 2.5. All these serve as evidence that soybean crops in maturity zone 3 have become less tolerant over time to drought conditions that occurred during the planting and early growing periods.

In contrast, only the coefficient of the trend variable is significant for relative maturity zone 4 ($\beta_{3,m=4}$), indicating that drought conditions had no effect on annual soybean yield in this zone.

In maturity zone 5, while drought conditions have an effect on soybean yield, the effect appear to be constant over time as shown by the insignificant coefficient of the trend variable ($\beta_{3,m=5}$). This indicates that soybean crops neither became more tolerant nor less tolerant to drought conditions during the planting and early growing periods in this zone—the marginal effect of drought conditions on yield was the same each year. Specifically from Equation 2.3, the significant and negative value of the intercept term ($\beta_{2,m=5}$) indicates that lower levels of the drought index had a negative effect on yield. The significant and positive coefficient of the quadratic form of the drought index variable ($\beta_{4,m=5}$), however, indicates that the effect of drought conditions on yield was improving as drought conditions increased, such that at higher levels of drought index, the effect on soybean yield is actually positive.

Drought Index for June and August

The period between June and August generally encompasses the flowering and pod setting periods of soybeans. Table 2.5 shows the model specification having a good fit with R-squared equal to 0.9541. The results shown in Column 4 indicates that soybean crops neither became more tolerant nor less tolerant to drought conditions in June to August for all maturity zones (i.e., the drought-trend term variable ($\beta_{3,m}$ for all $m =$

$1, 2, 3$) have insignificant coefficients). This result is the same as the result in maturity zone (5) for April to June.

Drought Index for August and October

Table 2.5 shows a good fit for the model specification (R-squared = 0.9469) for August and October, the period encompassing the seed development and maturity of soybeans. The table also shows that all coefficients for maturity zones 3 and 5 are significant Column (5).

Figure 2.4 shows the marginal effect of drought on annual soybean yield in maturity zone 3 over time using the years with the most non-zero marginal effects. The results are completely reversed from the effects of drought conditions in the early stages of the life of soybean planted in this zone (see Figure 2.3). First, while the effect of drought conditions on yield is negative, the effect gets smaller as the drought index gets higher. This means that as drought conditions worsen, yield actually improved. This is evident in Figure 2.4 through the positive slope of the trend in marginal effects across different years.

Second, the general effects of drought conditions on soybean yield improved through time. This is shown in Figure 2.4 by the upward shifts in the trends of the marginal effects across years. It is also evident in this figure that the negative effect of drought conditions on yield becomes less across time. This result is also supported by the significant and positive coefficient of the drought-trend interaction variable ($\beta_{3,m=3}$) in Table 2.5. All these indicate that soybean crops in maturity zone 3 have become more tolerant over time to drought conditions for the period encompassing the seed development and maturity of soybeans.

Figure 2.4. Marginal Effects of August to October Drought Index on Soybean Yield in Maturity Zone 3, Various Years

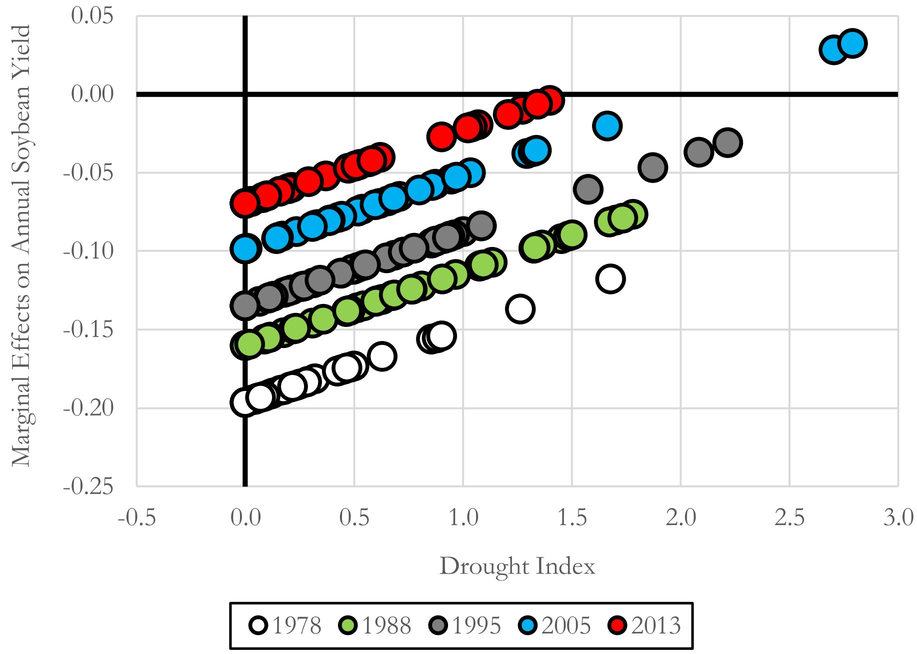
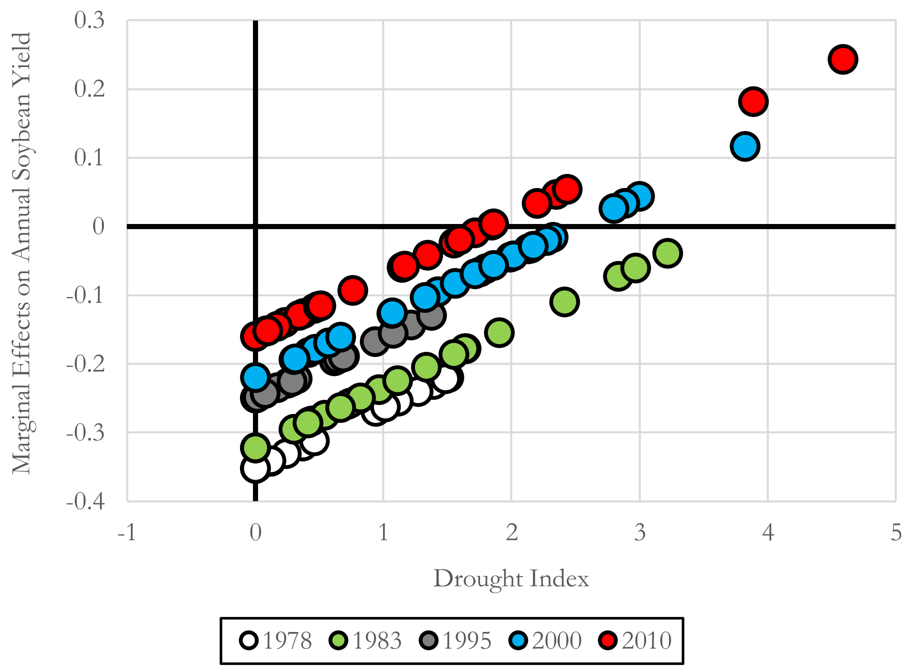


Figure 2.5. Marginal Effects of August to October Drought Index on Soybean Yield in Maturity Zone 5, Various Years



Similar results can be found in maturity zone 5 as shown in Figure 2.5. In particular, higher levels of drought index is associated with higher soybean yield. There are even many observations in 2000 and 2010 where higher drought conditions are associated with positive effects on soybean yield. The effect of drought condition on soybean yield also improves over time, as evidenced by the upward shifts in the annual trend of marginal effects. This result can also be seen from the positively significant coefficient of the drought-trend interaction term ($\beta_{3,m=5}$) in Table 2.5. In other words, soybean crops in maturity zone 5 are likewise more tolerant to drought conditions that occurred between August and October.

As for the effects of drought conditions that occurred between August and October on relatively maturity zone 4, results in Table 2.5 show all coefficients are significant except the quadratic form of the drought index. This means that the effects of drought conditions on soybean yield in maturity zone 4 is linear, such that the effect of drought conditions on yield is constant regardless of the intensity of the drought. Based on the negative sign of the coefficient on drought index, this effect is adverse: severe drought conditions are associated with lower yield. On a positive note, however, the coefficient on the interaction variable of drought index and time trend is positive. This indicates that the negative effect of drought on soybean yield is decreasing over time. In other words, soybean crops in maturity zone 4 also show increasing tolerance to drought conditions that occurred between August and October.

Clearly, there is evidence that soybean crops across all three relative maturity zones had become more tolerant to droughts conditions that occurred between August and October. An interesting question that would serve as follow-up worth exploring is:

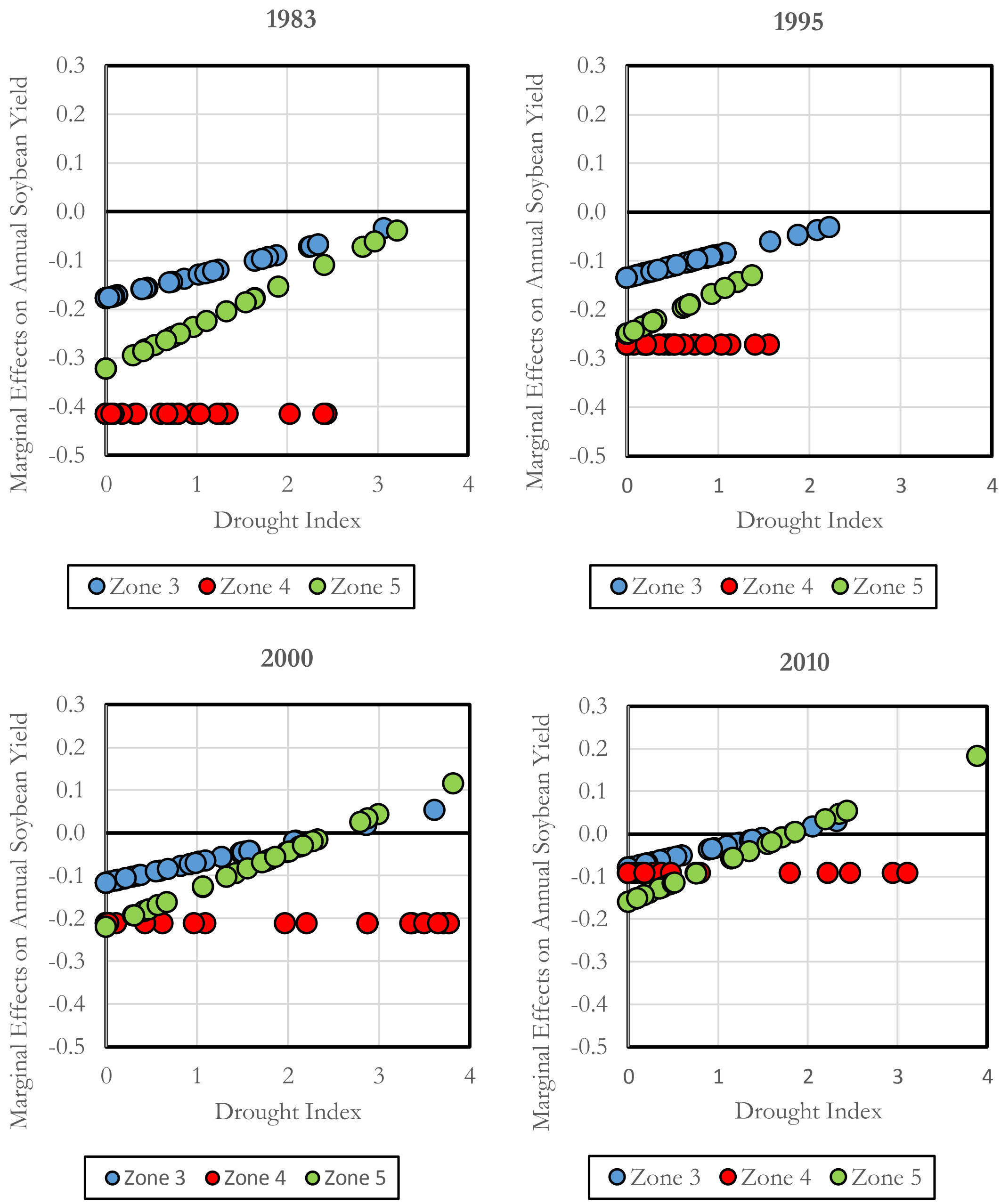
which relative maturity zone had soybeans that showed higher increases in drought-tolerance than other remaining relative maturity zones? A graphical analysis is used to answer this question.

Figure 2.6 shows four graphs corresponding to the years 1983, 1995, 2000, and 2010. Each graph shows the marginal effects of drought conditions on annual soybean yield across the three relative maturity zones. Similar to previous graphs, the four years are chosen based on the most nonzero marginal effects of drought conditions on soybean yield.

Each graph are scaled in exactly the same way so that any differences can be clear and distinct. As the preceding results have already shown, there is increasing tolerance to drought conditions across all three relative maturity zones. This is evident in the upward shifts in the marginal effects trends. In addition, except for soybeans planted in relative maturity zone 4, higher levels of drought index is associated with higher levels of soybean yield. This is evident in the upward slope in the marginal effects trends for observations in maturity zones 3 and 5.

What is more significant in the current analysis is the distinct differences in the magnitude of improvement in drought tolerance of soybeans across the three relative maturity zones. In particular, it is evident that the increases in drought tolerance for soybean crops planted in relative maturity zone 4 is larger than those in the other two relative maturity zones. Drought conditions had the worst effect on soybeans in relative maturity zone 4 in 1983 compared to those in the other two relative maturity zones. Through time, however, the soybean crops’ tolerance to drought conditions have dramatically increased such that lower levels of drought conditions have smaller effect on soybeans in relative maturity zone 4 than those in relative maturity zone 5.

Figure 2.6. Comparing Marginal Effects of August to October Drought Index Across the Three Relative Maturity Zones, Various Years



While soybean crops in relative maturity zone 3 are the least affected by drought conditions compared to those in the other two relative maturity zones, there is not much significant improvements in the crop's drought tolerance. For instance, while the improvement in drought tolerance of soybean crops in relative maturity zone 5 have been less than those in relative maturity zone 4, it has been better compared to those in relative maturity zone 3. As such, the gap between drought tolerance of soybeans in relative maturity zone 3 and relative maturity zone 5 are constantly closing until data in 2000 and 2010 show that at higher levels of drought conditions, the marginal effect on yield is positive and higher for soybeans in relative maturity zone 5. In summary, there is evidence that soybean crops in relative maturity zone 4 have seen the highest improvements in drought tolerance through time within the sample period. Soybean crops in relative maturity zone 5 comes second, whereas those in relative maturity zone 3 have seen the least improvement in drought tolerance.

2.6. Analyses and Conclusions

In this chapter, I attempt to fill a gap in the literature by testing the hypothesis established by Griliches (1957, 1958, 1960) on soybean seed innovation in the U.S. Guided by economic incentives, seed producers will invest in innovation where they expect profitability. One soybean seed trait that offers promise is drought tolerance. Analyzing three relative soybean maturity zones in the U.S., it is expected that seed innovation in drought tolerance will occur in lower numbered maturity groups considering that they capture a larger share of the U.S. market as well as producing higher yield levels (see Table 2.2). This means that among the three relative maturity zones being analyzed in this study, soybean crops in relative maturity zone 3 should exhibit the highest increase in drought-tolerance over time. Has drought tolerance, one important production trait in soybean seeds, given equal scientific attention between different growing regions of the U.S.?

Using panel-data regression techniques, I compared the change in drought-tolerance of soybean crops over time among three relative maturity zones in the U.S. Midwest. Increasing drought tolerance over time indicates investment has been made to innovate drought tolerance in soybean seeds. Table 2.6 summarizes the results of the panel-data regression analysis.

Quite contrary to expectations, soybean crops in maturity zone 3 exhibited improvements in tolerance only for droughts conditions that occurred between August and October. The soybean crops were showing decreasing tolerance to drought conditions that occurred between April and June, while there were no change in tolerance over time to drought conditions that occurred between June and August.

As for relative maturity zones 4 and 5, the effects of drought conditions between April and June were remarkably different than the effects in relative maturity zone 3. Whereas soybean crops in relative maturity zone 3 had become less drought tolerant to drought conditions, those in relative maturity zones 4 and 5 were not exhibiting any change at all in tolerance over time. In fact for soybean crops in relative maturity zone 4, drought conditions had no effect whatsoever on soybean yield.

With respect to the effects of drought conditions that occurred during the rest of the soybean plant's life cycle (June to October) in maturity zones 4 and 5, the results are similar to the results in maturity zone 3: soybean crops in relative maturity zone 4 and 5 exhibit no change in tolerance over time to drought conditions that occurred between June and August, but have become more tolerant over time to drought conditions that occurred between August and October.

Table 2.6. Summary of Regression Results

Maturity Zone	Drought Index		
	April to June	**June to August**	**August to October**
3	• Negative nonlinear effect of drought: Higher drought, lower yield • Soybean less drought-tolerant over time	• Positive nonlinear effect of drought: Higher drought, higher yield • No change in the effects of drought on yield over time	• Positive nonlinear effect of drought: Higher drought, higher yield • Soybean more drought-tolerant over time
4	• Drought has no effect on yield	• Positive nonlinear effect of drought: Higher drought, higher yield • No change in the effects of drought on yield over time	• Effect of drought is linear and negative • Soybean more drought-tolerant over time
5	• Positive nonlinear effect of drought: Higher drought, higher yield • No change in the effects of drought on yield over time	• Positive nonlinear effect of drought: Higher drought, higher yield • No change in the effects of drought on yield over time	• Positive nonlinear effect of drought: Higher drought, higher yield • Soybean more drought-tolerant over time

In summary, soybean crops had become more tolerant to drought conditions that occurred only between August and October. This result is very positive even if soybeans are not tolerant to drought conditions during other times of the year. This is because the period between August and October corresponds to a critical stage in a soybean plant's life when seeds develop and the pods reach maturity. This is the period when yield is significantly determined. The early portions of this period are also when the soybean plant is particularly sensitive to moisture stress. There are, however, differences in the improvement of drought tolerance over time among the three relative maturity zones. In particular, there is evidence that soybeans planted in relative maturity zone 4 have experienced the larger improvement in drought tolerance compared to the other two zones, while those in relative maturity zone 3 have experienced the least improvement. This is contrary to the hypothesis that seeds in lower-numbered relative maturity zones are expected to be given higher scientific attention with regards to innovations in drought tolerance given that there is potential for higher returns in these regions, and therefore soybeans in these regions should see highest improvements in drought tolerance.

Nevertheless, these differences in improvement of one important production trait in soybeans, drought tolerance, provides an indication that scientific attention have not been equal among different growing regions with regards to innovations in drought tolerance. These results may imply that the level of seed innovation for increasing tolerance to drought conditions may still not be enough given that the soybean crops are not becoming significantly more tolerant to droughts that occurred between April and August. While all soybean crops are showing increasing tolerance over time to drought conditions only between August and October, it is between June and August that soybean plants experience the highest average temperature during the year (see Table 2.2). Hence, it can be argued that there is a much higher need for innovation in soybean tolerance to drought conditions during this period.

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CHAPTER 3. MARGINAL IMPLICIT VALUES OF SOYBEAN

3. 1. Introduction

Historically, the soybean has been treated as a homogenous product. This is because soybean end value had not been so transparent, and at the same time, it has not been easy to tie end-user preferences with producer decision making. Recently, however, levels of soybean characteristics, or quality attributes, are increasing in economic importance. This emphasis on quality can be tied to buyers of commodities who are looking at market value as well as industries that utilize derived co-products from processing. Both are becoming more discriminating in their purchasing decisions (Barkema, 1993).[9] This has been made possible due to the technology available to soybean producers in changing seed nutrient composition through crop management, breeding methods, or genetic modifications (Bennett and Krishnan, 2005; Clemente and Cahoon, 2009). As a result, producers have increased price incentives in order to supply commodities with specific quality attributes (Parcell et al., 1995). For instance, as the animal industry becomes more competitive and cost-conscious, feed manufacturers become more judicious of the discern factors, such as protein found in soybean meal, in their purchased ingredients. Likewise, rising demand in edible oil relative to soybean supply has significantly increased oil value, underscoring the market potential of increasing oil content as a percentage of soybean seed weight. For instance, the latest oil crops outlook by the

[9] Edmeades (2007) distinguishes “attributes” from “characteristics,” where the former refers to features intrinsic in goods or traits found in plant varieties, while the latter refers to features of “households, farms, and production environment and markets.”

USDA Economic Research Service forecasts a stronger demand in the U.S. for 2014/2015, but with lower output due to lower oil extraction rate (Ash, 2015).

While spatial and temporal price variation creates more variation in soybean market prices, price differences also reflect variations in the presence and levels of quality attributes at a point in time and in a given location (Updaw et al., 1976). Prices are expected to vary as the levels of such quality attributes change. Aside from the demand factors discussed above, several supply factors also determine the level of these quality attributes as well. In particular, soybean quality attributes vary from north to south due to geographic and environmental factors, which in turn affects variation in soybean seed composition (Piper and Boote, 1999). The genetic makeup of soybeans, therefore, differs across geography. If differentiated quality is recognized through implicit premiums and discounts, regional price differences will vary by more than transportation costs.

In order to respond efficiently to pricing signals in producing soybeans with specific quality attributes desired by consumers, producers need to understand how these implicit values are determined, which ultimately affects the final price of soybeans. This is especially important considering that resources are being used to develop or improve varieties of soybeans that contain levels of quality attributes desired by both consumers and producers (Espinosa and Goodwin, 1991; Parcell et al., 1995). The United Soybean Board (2014), for example, conducted a survey of their membership and found that 66 percent favored a soybean component pricing system. Perrin (1980) distinguishes “commodity pricing,” where the price of a product does not take into account the amount of quality attributes (the “components” of the product) available in the product, from "component pricing," where the price of a product is based on the values of each of the quality attributes present in the product. The already extensive literature analyzing the implicit values of quality attributes of different agricultural commodities continues to be primarily dedicated to these issues.

Despite the importance of having knowledge on if and how commodity prices change as quality attribute levels change, very few studies relate to hedonic analysis on soybeans although a few of note include: Perrin (1980), Houston et al. (1981), and Murova et al. (1999). However, none of these have quantified the relationship of soybean price to two of soybean's most important quality attributes: protein content and oil content. Even though Lyford et al. (1997) and Hyberg et al. (1994) did hedonic analyses on soybean protein and oil content, their papers focused on the U.S. soybean export market.[10] There remains a gap in literature in terms of understanding relationship between soybean price and soybean protein and oil content in the U.S. domestic market.

This gap in the literature indicates that the soybean industry can benefit from further research in analyzing the two most important soybean quality attributes—protein and oil content. Gaining added knowledge on how commodity soybean prices change as quality attributes levels change will result in a schedule of implicit premiums and discounts associated with each marginal change in the levels of each of these two quality attributes. Such marginal implicit prices (or hedonic prices) can help soybean industry participants conduct cost-benefit analysis for investing in research to enhance quality attributes or to better segregate soybeans of different quality levels. In this chapter, I

[10] Lyford et al. (1997), in particular, estimated marginal values of soybean protein, oil, damaged kernels, foreign material, splits, and moisture across ten soybean exporting countries. Damage kernels and foreign material presence reduced prices, but other attributes were not statistically significant price determinants.

attempt to add to this research by estimating marginal implicit values of soybean protein and oil content and then analyzing the demand and supply factors that affect these values using a two-stage hedonic model based on U.S. state level data from 1993 to 2013. Using a hedonic price model in the first stage, the marginal implicit values of soybean protein and oil are estimated. In the second stage, a four-equation structural quality attributes model is used to analyze the demand and supply factors that affect the marginal implicit values and to shed more light on the relationship between soybean price and soybean quality attributes. One important feature of the two-stage hedonic regression method I employed in this paper is the inclusion of spatial competition in soybean quality attributes following the technique used by Parcell and Stiegert (1998). Inter-regional and intra-regional cross-state effects are included to analyze how protein and oil content in soybeans produced in other states affect the price of soybeans as well as implicit values of the two soybean quality attributes, protein content and oil content.

3.2. Review of Literature

Hedonic price theory asserts that the value of goods are derived from the quality attributes they possess. Taylor (1916), who analyzed cotton, wrote the earliest paper noting the link between quality and price. The literature that followed were primarily empirical in nature. The most noteworthy are landmark works by Waugh (1928), Court (1939), and Griliches (1961).[11] Lancaster (1966) provided the strong theoretical framework for subsequent empirical works on hedonic analysis, which was based on a "new theory of demand" stating that consumers not only demand goods, but they also

[11] Court (1939) is generally credited as being the first to use the term "hedonic."

demand the goods' quality attributes. Building upon Lancaster's work, Rosen (1974) further developed the hedonic price theory by incorporating market equilibrium properties into the analysis. Ladd and Martin (1976) and Ladd and Suvannunt (1976) later adapted the general theory and developed the theoretical foundations for performing hedonic analysis in agricultural products.

While other hedonic price theories consider the consumer goods approach where quality attributes provide the utility in a consumer's maximization problem (Houthakker, 1952; Theil, 1952; Lancaster, 1966; Rosen, 1974; Ladd and Suvannunt, 1976), Ladd and Martin (1976) used a different approach by adopting the neoclassical theory of a profit-maximizing firm where quality attributes are considered inputs in the production process.[12] A product is demanded by producers because of its unique set of quality attributes.[13] These theories have been used in many empirical studies that derive implicit values of quality attributes for different agricultural products.[14]

3.3. Theoretical Model

Following Ladd and Martin (1976), the solution to the profit maximization problem for the producer relates the price paid for a bushel of soybean to the values of the marginal

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[12] Despite this divergence, Espinosa and Goodwin (1991) explained that both utility-maximization and profit-maximization will yield the same hedonic price function.

[13] Ladd and Martin (1976) named their model the Input Characteristic Demand Model (ICM).

[14] Empirical studies on agricultural products include apples (Tronstad et al., 1992; Harper and Greene, 1993; Kajikawa, 1998; Carew, 2000; Carew et al., 2012), banana (Edmeades, 2007), barley (Wilson, 1984), beef cattle (Parcell et al., 1995; Wahl et al., 1995; Coatney et al., 1996; Dhuyvetter et al., 1996; Walburger, 2002), beef and pork (Parcell and Schroeder, 2007), bell peppers (Estes, 1986), cotton (Ethridge and Davis, 1982; Ethridge and Neeper, 1987; Bowman and Ethridge, 1984 and 1992; Chiou et al., 1993; Chen et al., 1997), fruits and vegetables (Misra et al., 1991; Estes and Smith, 1996), grapes (Golan and Shalit, 1993), milk (Lenz et al., 1994; Gillmeister et al., 1996), pork swine (Walburger and Foster, 1994; Melton et al., 1996), rice (Brorsen et al., 1984; Dalton, 2004), tobacco (Samikwa et al., 1998), tomatoes (Jordan et al., 1985; Bierlen and Grunewald, 1995), wheat (Bale and Ryan, 1977; Veeman, 1987; Hill, 1988; Espinosa and Goodwin, 1991; Ahmadi-Esfahani and Stanmore, 1994; Barkley and Porter, 1996; Parcell and Steigert, 1998), and wool (Nolan et al., 2013).

yields of the bushel's quality attributes.[15] The price paid (P) for a bushel of soybean ($/bushel) is equal to the sum of values of the marginal yields, which represent the bushel's quality attributes:

$$(3.1) \quad P = \sum_i V_i \times \frac{\delta Z_i}{\delta Q}$$

where V_i is the marginal implicit value of soybean quality attribute i, Z_i refers to total quantity of soybean quality attribute i, and Q is the quantity of available soybeans. $\partial Z_i / \partial Q$ is the marginal yield of quality attribute i.

It is generally accepted that, consistent with the reality of inputs, the marginal yield of quality attribute i is assumed to be constant. Specifically:

$$(3.2) \quad \frac{\partial Z_i}{\partial Q} = Z_i$$

It is reasonable, for example, that a one percentage point increase in protein content yields a one percentage point increase in protein for a bushel of soybean. Equation 3.1 can then be re-specified as:

$$(3.3) \quad P = \sum_i V_i Z_i$$

[15] See Ladd and Martin (1976) for a complete discussion on the derivation.

Regressing soybean price against soybean quality attributes to obtain the marginal implicit values of the quality attributes encompasses the first stage of Rosen's (1974) two-stage method. The implicit marginal value of quality attribute i is derived by differentiating $P(Z)$ with respect to the i^{th} argument, Z_i, and then evaluating the derivative at the level of total quantity of the soybean quality attribute:

$$(3.4) \quad P_i = \frac{\delta P}{\delta Z_i} = V_i$$

An innovation in Parcell and Stiegert (1998) captures how the value of a quality attribute in a given state is also affected by a change in the total availability of the same quality attribute in another soybean-producing state. This is because when the soybean crop in one state cannot supply an adequate volume of a particular quality attribute, processors may look to other states to source commodity soybeans with the desired quality attribute levels. Such "spatial competition" exists when geographic location is a significant factor influencing consumer preference. For example, suppose the Missouri soybean price (P_1) depends on availability of protein ($i = 1$)—not only in the Missouri soybean production (Z_{11}), but also in the Illinois soybean production (Z_{12}), and the Iowa soybean production (Z_{13}). Equation 3.3 for the price of a bushel of soybean in Missouri could be specified in a linear combination of regional protein levels to account for spatial competition among the protein attributes:

$$
\begin{aligned}
P_1 &= \beta_1 Z_{11} + \beta_2(Z_{11} \times Z_{12}) + \beta_3(Z_{11} \times Z_{13}) \\
&= (\beta_1 + \beta_2 Z_{12} + \beta_3 Z_{13})Z_{11} \qquad (3.5) \\
&= V_1 Z_{11} \qquad \text{where} \quad V_1 = \beta_1 + \beta_2 Z_{12} + \beta_3 Z_{13}
\end{aligned}
$$

β_1 represents the coefficient that captures how changes in Missouri soybean protein content affects Missouri soybean price; β_2 represents the coefficient relating changes in Illinois and Missouri soybean protein content to Missouri soybean price; β_3 represents the coefficient relating changes in Iowa and Missouri soybean protein content to Missouri soybean price; and, V_1 is the marginal implicit price of soybean protein in Missouri, which varies with the level of protein in Illinois and Iowa. In general, β_2 and β_3 are interpreted as inter-state effects that capture the impact on the price of soybeans in one state from changes in soybean attribute levels observed in other states. This implies that the value of a quality attribute in a given state is also determined by aggregate supply and aggregate demand for the given quality attribute. For example, protein and oil levels cannot generally be varied once they enter the manufacturer's production system. This provides a theoretical basis for modeling these quality attributes spatially.

Results from the first stage do not indicate the structure of the quality attributes' demand and supply markets. Rosen suggested that the marginal implicit pricing schedule that resulted from the first stage estimation only resembles the series of supply and demand equilibria with each point corresponding to different levels and combinations of supply and demand factors. I derived the information regarding the structure of consumer preferences and producer technologies that influence these equilibria by applying Rosen's second stage methodology. The second stage involves a structural quality attributes model consisting of equations that are determined simultaneously to estimate supply and demand functions of marginal implicit values of quality attributes:

$$P_i(Z) = f(Z_i, Z_{-i}, X) \quad \text{for supply} \tag{3.6}$$

$$P_i(Z) = g(Z_i, Z_{-i}, Y) \quad \text{for demand} \tag{3.7}$$

where P_i is the marginal implicit value of quality attribute i, which is generated from first-stage estimation results; Z_i is the quantity of soybean quality attributes i; Z_{-i} is the quantity of other soybean quality attributes; X is a set of factors that influence the supply of quality attribute i; and, Y is a set of factors that influence the demand for quality attribute i. The structural quality attributes model consists of $2 \times i$ equations, where i is the number of quality attributes being analyzed.

3.4. Empirical Model and Data

The first-stage equation to be estimated is the hedonic price model of soybeans:

$$\begin{aligned} Price_{it} = \sum_{i=1}^{n} \delta_i State &+ \alpha_1 Protein_{it} \\ &+ \alpha_2 Protein_{it}^2 + \alpha_3 (Protein_{it} \times Prt\_WR_{it}) \\ &+ \alpha_4 (Protein_{it} \times Prt\_OR_{it}) + \alpha_5 Oil_{it} + \alpha_6 Oil_{it}^2 \\ &+ \alpha_7 (Oil_{it} \times Oil\_WR_{it}) + \alpha_8 (Oil_{it} \times Oil\_OR_{it}) \\ &+ \alpha_9 Dummy2013_t + \varepsilon_{it} \end{aligned} \tag{3.8}$$

Variable definitions are presented in Table 3.1. The subscripts i and t refer to the state and year, respectively.

Equation 3.8 contains $n = 27$ binary terms representing state dummy variables to capture other state-specific factors that influence differences in soybean prices such as transaction costs and transportation costs. Because of the inclusion of dummy variables representing all soybean-producing states, the model is specified with no intercept term. The next four terms are the states' average protein content ($Protein_{it}$) and its quadratic term, which represents the interaction of state protein average and the harvest-weighted protein average of all states within the same region (Prt_WR_{it}). Finally, the interaction of state protein average and the harvest-weighted protein average of all states outside the region is represented by Prt_OR_{it}.

The next four terms follow a similar pattern of variables, where the soybean quality attribute is soybean oil content. These include Oil_{it} and its quadratic term for own-state, Oil_WR_{it} for harvest-weighted protein average in all states within the same region, and Oil_OR_{it} for harvest-weighted protein average in all states outside the region. Quadratic terms for the average protein and oil content are included to capture further nonlinearities in the relationship between soybean price and these two quality attributes.

The interaction variables aim to measure the inter-state availability of each soybean protein quality attribute and to account for inter-state effects of soybean price. In the case of the state of Missouri, which belongs to the North Central regional classification, the average level of protein content of other states belonging to the same region is the harvest-weighted average of protein content in Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio and Wisconsin combined.

Table 3.1. Summary Statistics: First-Stage Hedonic Price Model Variables

Variable names	Definition	Exp. effect on price	Ave	S.D.	Min	Max
State						
$Price_{it}$	Average soybean price in state i and year t deflated using 2014 CPI – all urban consumers (food and beverages only) (US$/bushel)		10.82	2.48	6.58	15.19
$Protein_{it}$	Average soybean protein content in state i and year t (%/bu)	+	35.29	1.09	30.40	40.10
Prt_WR_{it}	Harvest-weighted average of soybean protein content in all states within the same region at year t	–	35.18	0.84	30.40	37.40
Prt_OR_{it}	Harvest-weighted average of soybean protein content in all other states outside the region at year t	–	34.89	0.43	33.91	35.85
Oil_{it}	Average soybean oil content in state i and year t (%/bu)	+	18.84	0.70	16.65	21.20
Oil_WR_{it}	Harvest-weighted average of soybean oil content in all states within the region at year t	–	18.87	0.56	16.80	20.34
Oil_OR_{it}	Harvest-weighted average of soybean oil content in all other states outside the region at year t	–	18.83	0.32	18.22	19.42

Note: Also included but not shown are state dummy variables, (see Table 3.2 for the list of 27 U.S. states by region) and a dummy variable for the year 2013. Subscripts *i* and *t* denotes state and year (*t* = 2003, 2005, … , 2013), respectively. Number of samples: 297 (27 states, 11 years).

Table 3.2 lists the states included in the analysis together with their corresponding assigned regions.

Table 3.2. Soybean-Producing States Included in this Study

Region[1]	States[2]
Delta	Arkansas, Louisiana and Mississippi
North Central	Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio and Wisconsin
Northeast[3]	Delaware, Maryland, New Jersey, New York, Pennsylvania, Virginia
Northern Plains	Kansas, Nebraska, North Dakota*, and South Dakota
Southeast	Alabama*, Kentucky, North Carolina and Tennessee
Southwest[3]	Oklahoma, Texas

Notes:

1. Regional delineation are based on classification by the Economic Research Service of the U.S. Department of Agriculture (USDA-ERS). Documentation can be found on this webpage: http://www.ers.usda.gov/data-products/commodity-costs-and-returns/documentation.aspx. States were grouped according to those with similar production practice and resource characteristics.
2. States marked with "*" are not specified to be included in the assigned region based on the classification of the USDA-ERS. In this study, they are instead included in the corresponding regions based on proximity.
3. The regions Northeast and Southwest are not classified by the USDA-ERS. These regions were instead generated for this study, and it is assumed that the corresponding states are included based on similar production practices and resource characteristics.

The regional classifications are adopted from the soybean regional definitions provided by the USDA Economic Research Service.[16] The states were classified "according to those with similar production practice and resource characteristics." Finally, a binary variable with a value equal to 1 for observations occurring in 2013 and 0 otherwise is included to capture the decrease in soybean values in 2013. The decrease in prices was attributed to increased soybean production (USDA Economic Research Service, 2014).

[16] See http://www.ers.usda.gov/data-products/commodity-costs-and-returns/documentation.aspx.

The inclusion of quadratic and interaction terms of the quality attributes makes the relationship between soybean price and soybean quality attributes nonlinear as specified in Equation 3.8. This helps avoid problems associated with estimating the first-stage equation using a linear functional form as discussed by Witte et al. (1979), Mendelsohn (1984, 1985, and 1987), and Kahn and Lang (1988). These authors showed that using a linear functional form will yield constant marginal implicit values independent of the quantity of the quality attributes.

Differentiating the hedonic price Equation 3.8 with respect to protein and oil content yields the marginal implicit prices of protein and oil, respectively:

$$\text{(3.9)} \quad \frac{\partial Price_{it}}{\partial Protein} = \alpha_1 + 2\ \alpha_2\ Protein_{it} + \alpha_3\ Prt\_WR_{it} + \alpha_4\ Prt\_OR_{it}$$

$$\text{(3.10)} \quad \frac{\partial Price_{it}}{\partial Oil} = \alpha_5 + 2\ \alpha_6\ Oil_{it} + \alpha_7\ Oil\_WR_{it} + \alpha_8\ Oil\_OR_{it}$$

As Equations 3.9 and 3.10 show, the state marginal implicit prices of protein and oil are not constant and instead depend on the quantity levels of the state's (Missouri's) own protein and oil content, respectively, as well as the protein and oil content of other states, respectively. This nonlinearity is partly aimed to capture spatial competition in soybean quality attributes.

Soybean protein and oil content are expected to be related positively to price. Protein and oil are the most critical components sought by soybean crushers. Soybean protein content is a predictor of how well the soybean meal will yield digestible protein.

Soybean oil content is a prediction of oil value to be sold for conversion to fuel or food use. Increases in the level of protein content or oil content in adjacent states would be expected to decrease price in state i. Similarly, an increase in the level of protein content or oil content in all other states would be expected to decrease the price in state i.

As is in standard econometric analysis involving time series data, I conducted several tests to verify if soybean price, protein content, and oil content are each stationary. The unit root tests I employed include those based on methods of Harris and Tzsavalis (1999) and Breitung (2000), as well as the Fisher-type tests outlined by Choi (2001). The results show that the data are stationary.

When using panel data, cross-sectional heteroskedasticity, time-series autocorrelation, and cross-panel dependence are typical concerns. I tested the null hypothesis of homoskedasticity versus the alternative of group-wise heteroskedasticity using the modified Wald test (Greene, 2000). The results show that there is no evidence to reject the null hypothesis of equal variances between states. To test for autocorrelation, I used a Wald test proposed by Wooldridge (2002). This procedure resulted in the rejection of the null hypothesis of no autocorrelation. Finally, to test for cross-panel dependence, I used the CD tests proposed by Pesaran (2004). The results rejected the null hypothesis of no cross-sectional dependence. This means that the cross-sectional units are not independent. To summarize, due to the existence of autocorrelation and cross-sectional dependence in the data, Equation 3.8 was estimated using pooled feasible generalized least squares. The estimators were transformed using Prais and Winsten (1954) methodology to account for the autocorrelation, with the standard errors panel-corrected to account for cross-panel dependency. Once the parameters were estimated, a total of 297 marginal implicit prices for each of soybean protein and oil content were calculated using Equations 3.9 and 3.10 (one marginal implicit price for each of the 27 states and for each of the 11 years, 2003 to 2013).

The marginal implicit prices were used as endogenous variables in the second-stage estimation of the system of structural quality attributes equations. The structural soybean quality attributes inverse demand equation is expressed as:

$$\begin{aligned} MIP_{jit} = {} & \beta_{j1} Protein_{it} + \beta_{j2} Prt\_Ratio\_WR_{it} \\ & + \beta_{j3} Prt\_Prd\_Ratio\_WR_{it} + \beta_{j4} Prt\_Ratio\_OR_{it} \\ & + \beta_{j5} Prt\_Prd\_Ratio\_OR_{it} + \beta_{j6} Oil_{it} \\ & + \beta_{j7} Oil\_Ratio\_WR_{it} + \beta_{j8} Oil\_Prd\_Ratio\_WR_{it} \\ & + \beta_{j9} Oil\_Ratio\_OR_{it} + \beta_{j10} Oil\_Prd\_Ratio\_OR_{it} \\ & + \beta_{j11} Post2007_t + \mu_{jit} \end{aligned} \tag{3.11}$$

Variable definitions are presented in Table 3.3. In the structural quality attributes inverse demand equation, the marginal implicit price of the quality attributes ($j = Protein, Oil$) is expressed as a function of own levels of protein and oil content, the relative levels of protein and oil content in other states, the total production of own protein and oil content relative to other states, and one demand-shift exogenous variable related to the periods of biodiesel production.

Table 3.3. Summary Statistics: Second-Stage Structural Inverse Quality Attributes Demand Equation Variables

Variable names	Definition	Ave	S.D.	Min	Max
$MIP_{PROTEIN_{it}}$	Marginal implicit price of protein (protein premium) in state i and year t estimated from first-stage hedonic price model (2014 US$/bushel)	1.25	0.0760	1.04	1.47
$MIP_{OIL_{it}}$	Marginal implicit price of oil (oil premium) in state i and year t estimated from first-stage hedonic price model (2014 US$/bushel)	1.63	0.1216	1.40	1.87
$Prt\_Ratio\_WR_{it}$	Ratio of harvest-weighted average protein content in all other states within the same region to the harvest-weighted average protein content in state i at year t	1.00	0.0308	0.84	1.19
$Prt\_Ratio\_OR_{it}$	Ratio of harvest-weighted average protein content in all other states not in the same region to the harvest-weighted average protein content in state i at year t	1.00	0.0287	0.89	1.17
$Prt\_Prd\_Ratio\_WR_{it}$	Ratio of total production of protein (total soybean harvest multiplied by average protein content) in state i to total production of protein of all other states within the same region at year t	0.36	0.4334	0.02	3.55
$Prt\_Prd\_Ratio\_OR_{it}$	Ratio of total production of protein (total soybean harvest multiplied by average protein content) in state i to total production of protein of all other states not belonging to the same region at year t	0.04	0.0412	< 0.00	0.17
$Oil\_Ratio\_WR_{it}$	Ratio of harvest-weighted average oil content in all other states within the same region to the harvest-weighted average oil content in state i at year t	1.00	0.0357	0.85	1.18
$Oil\_Ratio\_OR_{it}$	Ratio of harvest-weighted average oil content in all other states not in the same region to the harvest-weighted average oil content in state i at year t	1.00	0.0350	0.88	1.13
$Oil\_Prd\_Ratio\_WR_{it}$	Ratio of total production of oil (total soybean harvest multiplied by average protein content) in state i to total production of oil of all other states within the same region at year t	0.36	0.4017	0.02	2.93
$Oil\_Prd\_Ratio\_OR_{it}$	Ratio of total production of oil (total soybean harvest multiplied by average protein content) in state i to total production of oil of all other states not belonging to the same region at year t	0.04	0.0415	< 0.00	0.17

Note: Also included but not shown are first stage variables $Protein_{it}$ and Oil_{it} (see Table 3.1 for the description), state dummy variables (see Table 3.2 for the list of 27 U.S. states by region) and $Post2007_t$, a variable that takes on the value of 1 for observations in year 2007 onwards, and 0 otherwise. Subscripts i and t denotes state and year (t = 2003, 2005, … , 2013), respectively. Number of samples: 297 (27 states, 11 years).

As is standard in demand models, the marginal implicit value of quality attribute j is expected to be inversely related to its own content level. The ratios of other states' average protein and oil content to the average protein and oil content in own-state, respectively, are included to account for cross-state effects. It is expected that there is also an inverse relation, with the marginal implicit prices decreasing as the relative protein and oil content in soybeans of other states are higher, resulting in demand being pulled away from own-state's soybeans. An increase in the ratio of total production of protein and oil in own-state indicates an increase in the quantity of available protein and oil, which should lead to a decrease in the value of each of these two quality attributes, respectively.

The inclusion of both protein variables and oil variables in each of the two structural quality attributes inverse demand equations follows Rosen's (1974) idea that commodities are bundles of characteristics or attributes that are incompletely separable from each other. This means that the level of one attribute may affect the marginal implicit value of another attribute. This is particularly true for soybeans. The value of protein in soybeans, for example, is derived from the value of soybean meal. The value of soybean meal is partly influenced by the oil content of soybeans since the amount of meal is determined by how much dry matter remains after oil is extracted from soybeans (Updaw et al., 1976). Other studies also identify a negative correlation between the amount of protein content and the amount of oil content in soybeans (Dornbos and Mullen, 1992; Chung et al., 2003).

$Post2007_t$ is a variable that equals 1 for years prior to 2007 and 0 otherwise, and it is included to capture two factors that might be affecting the demand for soybeans from

2007 onwards. First, U.S. biodiesel production increased dramatically during the mid-2000s, from less than 10 million gallons in 2003 to 40 million gallons in 2007. Soybean oil, has been the largest feedstock used in the production of biodiesel. Biodiesel's introduction and use may represent a structural change that alters the demand for soybeans. In particular, increased demand for soybean oil due to increased production of biodiesel would raise the value of oil in soybeans. The increase in the value of soybean oil may prompt producers to move away from protein production and into oil production. As such, this shift in demand may change the value of protein in soybeans. Second, dried distillers' grains (DDG) from corn, which is a byproduct of the biodiesel production process, have increased in use as an alternative livestock feed. The additional shift in demand away from soybean meal for use in livestock feed may further change the value of soybean protein. Thus, this decrease in demand for soybean meal would decrease the value of protein in soybeans.

Slightly deviating from Rosen's specification, however, the structural supply equation for soybean quality attributes adopts the approach of Bowman and Ethridge (1992) and Chiou et al. (1993). This alternative approach hypothesizes that the supply of attributes is quantity-dependent instead of price-dependent. Agricultural commodity markets are generally characterized by lags in the production process. As such, the market for soybean attributes is not modeled as the simultaneous system of demand and supply equations suggested by Rosen. The departure comes in the use of a structural direct supply equation, where each soybean attribute is expressed as a function of the marginal implicit prices and a set of supply shifters. Variations in these quality attributes, in particular, are influenced by environmental and climatic factors, which are location-specific (Vollmann et al., 2000; Hammond et al., 2005). The levels of protein and oil in soybeans are therefore hypothesized to be a function of weather factors in this paper. The structural soybean quality attributes supply equation is expressed as:

$$
\begin{aligned}
(3.12)\qquad Attribute_{jit} = {} & \gamma_{j1} MIP_{Protein_{it}} + \gamma_{j2} MIP_{Oil_{it}} + \gamma_{j3} Temp\_Apr\_Jun_{it} \\
& + \gamma_{j4} Temp\_Jun\_Aug_{it} + \gamma_{j5} Temp\_Aug\_Oct_{it} \\
& + \gamma_{j6} Precip\_Apr\_Jun_{it} + \gamma_{j7} Precip\_Jun\_Aug_{it} \\
& + \gamma_{j8} Precip\_Aug\_Oct_{it} + \gamma_{j9} Precip\_Annual_{it-1} \\
& + \gamma_{j10} TREND + \varphi_{jit}
\end{aligned}
$$

Table 3.4 presents the definition of variables in Equation 3.12. The inclusion of both marginal implicit prices of protein and oil in each of the two structural quality attributes supply equations indicate that the increase in the value of one quality attribute may provide an incentive to the producer to concentrate resources to producing more of the said attribute and less of the other attribute. To distinguish how weather variables impact the development of soybean quality attributes ($j = Protein, Oil$) at different stages of the soybean's life cycle, the structural quality attributes supply equations include average temperature and total precipitation variables measured between April and June, between June and August, and between August and October. Total precipitation during the previous year is also included to represent how production decisions are affected by producer's weather expectations.

Table 3.4. Summary Statistics: Second-Stage Structural Quality Attributes Supply Equation Variables

Variable names	Definition	Ave	S.D.	Min	Max
$MIP_{PROTEIN_{it}}$	Marginal implicit price of protein (protein premium) in state i and year t estimated from first-stage hedonic price model (2014 US$/bushel)	1.25	0.0760	1.04	1.47
$MIP_{OIL_{it}}$	Marginal implicit price of oil (oil premium) in state i and year t estimated from first-stage hedonic price model (2014 US$/bushel)	1.63	0.1216	1.40	1.87
$Temp\_Apr\_Jun_{it}$	Average daily temperature between April and June in state i and year t (degrees Fahrenheit)	62.98	6.27	49.30	76.50
$Temp\_Jun\_Aug_{it}$	Average daily temperature between June and August in state i and year t (degrees Fahrenheit)	74.11	5.00	62.60	86.80
$Temp\_Aug\_Oct_{it}$	Average daily temperature between August and October in state i and year t (degrees Fahrenheit)	65.75	5.68	54.90	77.70
$Precip\_Apr\_Jun_{it}$	Total precipitation from April to June in state i and year t (inches)	12.06	3.79	3.24	26.08
$Precip\_Jun\_Aug_{it}$	Total precipitation from June to August in state i and year t (inches)	12.14	3.60	2.46	23.22
$Precip\_Aug\_Oct_{it}$	Total precipitation from August to October in state i and year t (inches)	10.90	3.93	2.15	26.98
$Precip\_Annual_{it-1}$	Total annual precipitation in state i and year t-1 (inches)	40.51	12.74	13.36	73.78

Note: Descriptions and statistics for $MIP_{PROTEIN}$ and MIP_{OIL} are exactly those found in Table 3.3 and are duplicated here. Also included but not shown are first stage variables $Protein_{it}$ and Oil_{it} (see Table 3.1 for the description), state dummy variables (see Table 3.2 for the list of 27 U.S. states by region) and a trend variable. Subscripts *i* and *t* denotes state and year (*t* = 2003, 2005, … , 2013), respectively. Number of samples: 297 (27 states, 11 years).

Finally, soybean varieties may improve over time due to their natural adaptation to adverse environmental conditions through plant breeding or through biotechnology. Their varietal improvement over time is captured through the time trend variable.

Due to possible correlation in the error terms among the structural quality attributes' inverse demand and direct supply equations, the second-stage system is estimated using Zellner's (1962) seemingly unrelated regression (SUR) technique.

Data used in our analysis is represents an annual record spanning 11 years from 2003 to 2013 for 27 soybean-producing states (see Table 3.2 for the list of states). The use of panel data, which essentially consists of spatially and temporally distinct markets, helps alleviate the single market identification problem discussed by Brown and Rosen (1984), Mendelsohn (1984), Palmquist (1984), Epple (1987), and Edmeades (2007). Annual (marketing year) state average soybean price data was downloaded from the National Agricultural Statistics Service of the U.S. Department of Agriculture. To account for inflation and to express annual prices to an equivalent basis, the prices were converted to 2014 equivalent dollars by deflating the nominal values using all urban consumer price indexes for food and beverages as the deflator.[17] For the state-level average soybean protein and oil content, we used a rich dataset from the series of Soybean Quality Reports prepared for the American Soybean Association and the U.S. Soybean Export Council (U.S. Soybean Export Council, 2014). Temperature and precipitation data were downloaded from the National Climatic Data Center of the National Oceanic and Atmospheric Administration.

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[17] Data on monthly consumer price index (all urban consumers) (1982=100) were downloaded from the Bureau of Labor Statistics website of the U.S. Department of Labor (accessed July 4, 2015).

3.5. Results

The econometric estimates of hedonic price Equation 3.8 are reported in Table 3.5. The model explained more than 99% of the variation in soybean prices (model R-squared). All the variables except the quadratic terms of the soybean oil are significant and have the expected signs.

Soybean protein and oil content are related positively to own-state's price. This means that higher levels of protein and oil content in soybeans are associated with higher soybean prices. In terms of magnitude, the coefficient on own-state soybean oil content ($9.07/bushel in 2014 dollars) is greater than the coefficient on own-state soybean protein content ($6.66/bushel in 2014 dollars). These results should not be interpreted as oil content having greater effect on soybean price than protein content because such conclusion is conditional on the interaction terms. Both average soybean protein and oil content in states within the same region as well as states from other regions are negatively correlated to own-state soybean prices. This means that, as protein and oil content in soybeans produced in other states increase, the price of own-state soybeans declines. This indicates the presence of spatial competition in soybean quality attributes. The stark difference can be found in the magnitude of the cross-quantity effects. The coefficients show that the effect of both protein and oil content of soybeans from other region states are larger than those from within the same region. This should not be surprising given that the soybean quality attributes from a larger geographic area (all other states outside the region) should affect own-state soybean prices more than those from a smaller geographic area (states within the region).

Table 3.5. First-Stage Hedonic Price Model for Soybeans

Variables	Coefficient	Panel-Corrected Std. Err.
Protein Content		
$Protein_{it}$	6.6635 ***	1.8303
$Protein_{it}^2$	– 0.0437 *	0.0255
Prt_WR_{it}	– 0.0081 **	0.0035
Prt_OR_{it}	– 0.1027 ***	0.0150
Significant data points [a]	100%	
Mean Marginal Price	1.25	
Standard deviation	0.0760	
95% confidence interval [b]	[0.91, 1.59]	
Oil Content		
Oil_{it}	9.0650 ***	2.8986
Oil_{it}^2	– 0.0534	0.0759
Oil_WR_{it}	– 0.0304 ***	0.0107
Oil_OR_{it}	– 0.3641 ***	0.0327
Significant data points [a]	100%	
Mean Marginal Price	1.63	
Standard deviation	0.1216	
95% confidence interval [b]	[1.09, 2.18]	
R-squared	0.9969	

Notes:

a. Dependent variable: Soybean price deflated to 2014 values using consumer price index – all urban consumers (food and beverages only).
b. Significant data points refers to the percentage of marginal implicit prices that are statistically significant and of the expected sign.
c. Confidence intervals calculated using Chebychev's inequality: $\mu \pm \sigma\sqrt{k}$ where $k = \sqrt{20}$ for 95%.
d. ***, **, * denote coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
e. Also included in the regressions but not shown are state dummy variables and binary variable with value equal to 1 for observations in 2013 and 0 otherwise.
f. Number of samples: 297 (27 states with data spanning 11 years, from 2003 through 2013).

As the focus of this research, the marginal implicit prices are calculated using Equations 3.9 and 3.10 for protein and oil content, respectively.[18] All calculated values in 2014 dollars are significantly different from zero and of the right sign, with a mean of \$1.25/bushel for protein marginal value and \$1.63/bushel for oil marginal value. Using Chebyshev's inequality, the 95 percent confidence interval for protein marginal implicit price in 2014 dollars is between \$0.91/bushel and \$1.59/bushel, while that of oil marginal implicit price is between \$1.09/bushel and \$2.18/bushel. Figures 3.1 and 3.2 graphically trace the marginal implicit pricing schedule for soybeans and the protein and oil content, respectively. As Rosen (1974) warns, the relationships should not be interpreted as the downward sloping demand curve. Instead, each point in Figures 3.1 and 3.2 traces a sequence of equilibrium points, which represent the results from the shifting of supply of and demand for soybean protein and soybean oil due to changes in exogenous factors.

Using the derived protein and oil premium gradients as dependent variables in the two structural quality attributes inverse demand Equations 3.11 and two structural quality attribute supply Equations 3.12, the results in Tables 3.6 and 3.7 show how demand and supply factors affect the marginal implicit prices of soybean protein and oil.

For the structural quality attribute inverse demand equations in Table 3.6, an increase in own-state protein and oil levels decrease protein and oil premia, respectively. Using 2014 prices, a one-percentage point increase in own-state average protein content would decrease protein premium by \$0.07/bushel, while a one-percentage point increase in own-state average oil content would decrease oil premium by \$0.18/bushel.

[18] From the econometric results of estimating Equation 3.8, the coefficients of Oil_{it}^2, α_6, is not significantly different from zero. As such, in calculating the marginal implicit prices, Equation 3.10 is modified to exclude the term $2 \times \alpha_6 \times Oil_{it}$.

Figure 3.1. Estimated Soybean Protein Marginal Implicit Pricing Schedule from First-Stage Hedonic Pricing Equation

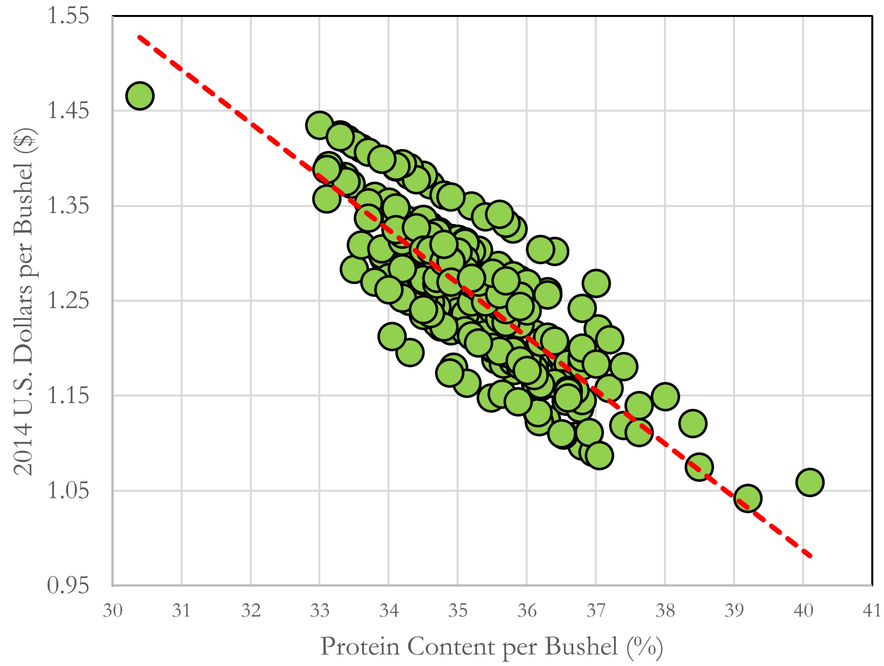
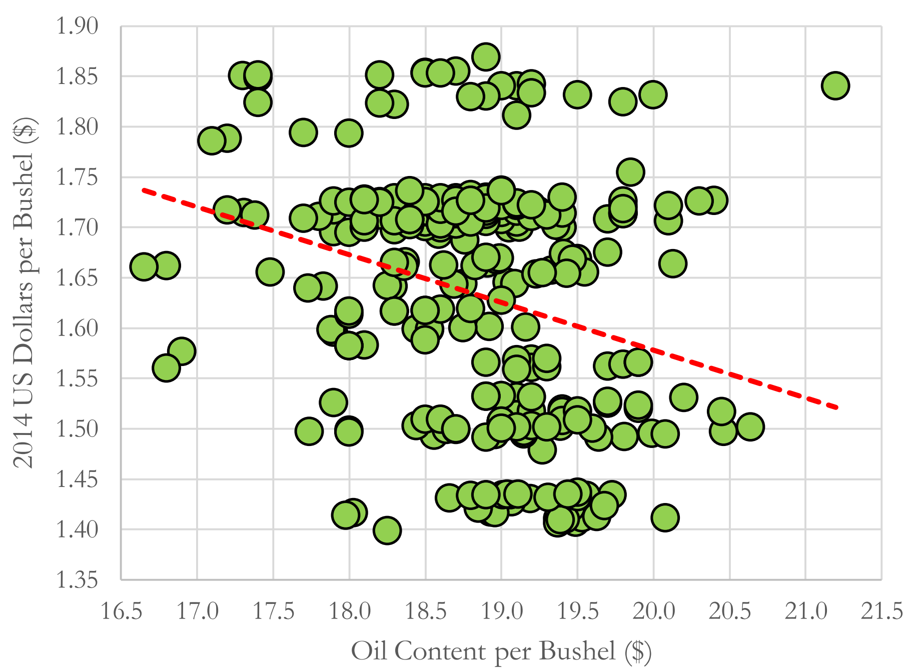


Figure 3.2. Estimated Soybean Oil Marginal Implicit Pricing Schedule from First-Stage Hedonic Pricing Equation



As expected, the cross-characteristic effects show substitutability between protein and oil contents. Increasing the level of oil content by one percent would increase protein premium by $0.01/bushel, while increasing the level of protein content by one percent would increase oil premium by $0.13/bushel. Looking at other demand factors that affect the marginal implicit value of protein, the average protein ratio and average oil ratio relative to states from other regions are significant. An increase in the protein content of soybeans in states from other regions relative to the average protein content of own-state would decrease the value of protein.

On the other hand, an increase in the oil content of soybeans in states from other regions relative to the average oil content of own-state would increase the value of protein. These two results lend further support to the presence of spatial competition in soybean quality attributes.

As for the demand factors that affect the marginal implicit value of oil, all the variables are significant except for the ratio of the average protein and oil content of other states from the same region relative to own-state average protein and oil content. In particular, the results still indicate the presence of spatial competition in soybean quality attributes.

The coefficients of $Post2007_t$ in both demand equations are significant and positive. This may be interpreted as resulting from increased production of biodiesel, which uses soybean oil as one of its major feedstocks. This increase in demand would raise the value of soybean oil.

Table 3.6. Second-Stage Structural Inverse Demand Model for Soybean Quality Attributes

Explanatory Variables	Dependent Variable $MIP_{PROTEIN_{it}}$	$MIP_{OIL_{it}}$
$Protein_{it}$	– 0.0679 *** (0.0023)	0.1277 *** (0.0048)
Oil_{it}	0.01235 *** (0.0041)	– 0.1816 *** (0.0087)
$Prt\_Ratio\_WR_{it}$	0.0228 (0.0921)	– 0.2426 (0.1893)
$Prt\_Prd\_Ratio\_WR_{it}$	0.0482 (0.0484)	– 0.2104 ** (0.0991)
$Prt\_Ratio\_OR_{it}$	– 0.8690 *** (0.0023)	4.1627 *** (0.2448)
$Prt\_Prd\_Ratio\_OR_{it}$	1.8814 (1.3057)	– 5.7147 ** (2.6749)
$Oil\_Ratio\_WR_{it}$	0.0367 (0.0719)	– 0.1443 (0.1477)
$Oil\_Prd\_Ratio\_WR_{it}$	– 0.0527 (0.0517)	0.2258 ** (0.1059)
$Oil\_Ratio\_OR_{it}$	2.1010 *** (0.1024)	– 3.3003 *** (0.2134)
$Oil\_Prd\_Ratio\_OR_{it}$	– 1.8119 (1.3016)	5.4863 ** (2.6667)
$Dummy2007_t$	0.0431 *** (0.0034)	0.1194 *** (0.0073)
RMSE	0.0289	0.0625
R-squared	0.9995	0.9985

Notes:

a. Standard errors in parentheses.
b. ***, **, * denote coefficient is significantly different from zero at the 1%, 5%, 10% levels, respectively.
c. Number of samples: 297 (27 states with data spanning 11 years, from 2003 through 2013)

Table 3.7. Second-Stage Structural Supply Model for Soybean Quality Attributes

	Dependent Variable	
Explanatory Variables	$Protein_{it}$	Oil_{it}
$MIP_{PROTEIN_{it}}$	5.9773 *** (0.8864)	8.7151 *** (0.3696)
$MIP_{OIL_{it}}$	8.6295 *** (0.5806)	1.8525 *** (0.2420)
$Temp\_Apr\_Jun_{it}$	– 0.2705 *** (0.0397)	– 0.0020 (0.0166)
$Temp\_Jun\_Aug_{it}$	0.3599 *** (0.0568)	0.0159 (0.0237)
$Temp\_Aug\_Oct_{it}$	0.0406 (0.0449)	0.0585 *** (0.0188)
$Precip\_Apr\_Jun_{it}$	– 0.0666 *** (0.0255)	– 0.0024 (0.0107)
$Precip\_Jun\_Aug_{it}$	0.1427 *** (0.0315)	0.0078 (0.0132)
$Precip\_Aug\_Oct_{it}$	0.1017 *** (0.0247)	0.0493 *** (0.0103)
$Precip\_Annual_{it-1}$	0.0159 * (0.0082)	0.0019 (0.0034)
$TREND$	– 0.2175 *** (0.0272)	– 0.1139 *** (0.0113)
RMSE	1.3987	0.5804
R-squared	0.9984	0.9991

Notes:

a. Standard errors in parentheses.
b. ***, **, * denote coefficient is significantly different from zero at the 1%, 5%, 10% levels, respectively.
c. Number of samples: 297 (27 states with data spannng 11 years, from 2003 through 2013)

As expected from the results of the structural soybean quality attributes supply equations in Table 3.7, soybean protein and oil content are each positively related to their marginal implicit prices. With respect to weather factors, higher temperature measurements between April and June significantly affect soybean protein content negatively, while the effect is significant and positive between June and August. The result for drought conditions between June and August are consistent with the findings of several studies. Wolf et al. (1982), Dombos and Mullen (1992), Mullen and Dombos (1992), Gibson and Mullen (1996), and Piper and Booth (1999) find a direct relationship between temperature and protein content: higher levels of temperature increase protein content. Higher levels of precipitation significantly affect soybean protein content negatively between April and June, and then positively between June and October. With respect to soybean oil, both temperature and precipitation are significant factors only between August and October. Higher temperature and precipitation levels during this period increase oil content in soybeans. Finally, the previous year's precipitation levels are significant in affecting only soybean protein content and the effect is positive.

Finally, the time trend variable significantly affects b oth soybean quality attributes negatively. This could indicate an actual decline in soybean variety improvement throughout the sample period.

3.6. Summary and Conclusions

Quality attributes of soybeans are becoming more important as markets realize its impact in relation to usage. Soybean protein level impacts animal feed efficiency and soybean oil content signifies the amount of oil to be used for food, fuel or industrial purposes (e.g. biofuels). Because different soybean prices reflect variations in the level of soybean quality attributes, quantifying the impacts of these quality-price differences is essential so that the soybean industry understands the implicit-value of enhancing trait levels within a component pricing system. Equally important is identifying the demand and supply factors that influence the marginal implicit values of these two soybean quality attributes. This paper accomplishes this by using a two-stage hedonic model to estimate the marginal implicit values of soybean protein and oil and to identify demand and supply factors that affect these implicit values. The possibility of existence of spatial competition in soybean quality attributes among different soybean-producing states is especially considered in this analysis.

The results of the hedonic price model suggest that there is indeed an incentive for U.S. farmers to produce soybeans with higher quantities of protein and oil. Marginal implicit values of soybean protein in 2014 dollars range from \$0.91/bushel to \$1.59/bushel, whereas the marginal implicit values of soybean oil range from \$1.09/bushel to \$2.18/bushel. The important additional insight from the foregoing analysis is finding that spatial competition in soybean quality attributes exist. Higher levels of average protein and oil content in other states negatively impact the price of soybean and the marginal values of protein and oil in own-state.

These findings are particularly important given the seeming general disconnect between demand and supply: farmers are focused on maximizing yields, while customers care only about the soybean quality attributes, especially protein and oil (Illinois Soybean Board, 2014). Gaining knowledge of the value of these soybean quality attributes can help farmers' bottom line by providing insights on what buyers and other producers value more. Appreciating how these implicit values are determined can help producers respond efficiently to pricing signals in producing soybeans with specific quality attributes desired by consumers and other producers. Finally, understanding the effect of soybean quality to price can boost U.S. market share in the global trade for soybeans considering the increasing importance of high-quality products to U.S. foreign customers (see for example, Hyberg and Uri, 1996).

3.7. References

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CHAPTER 4. AN EMPIRICAL ANALYSIS OF DEMAND FOR U.S. SOYBEANS IN THE PHILIPPINES

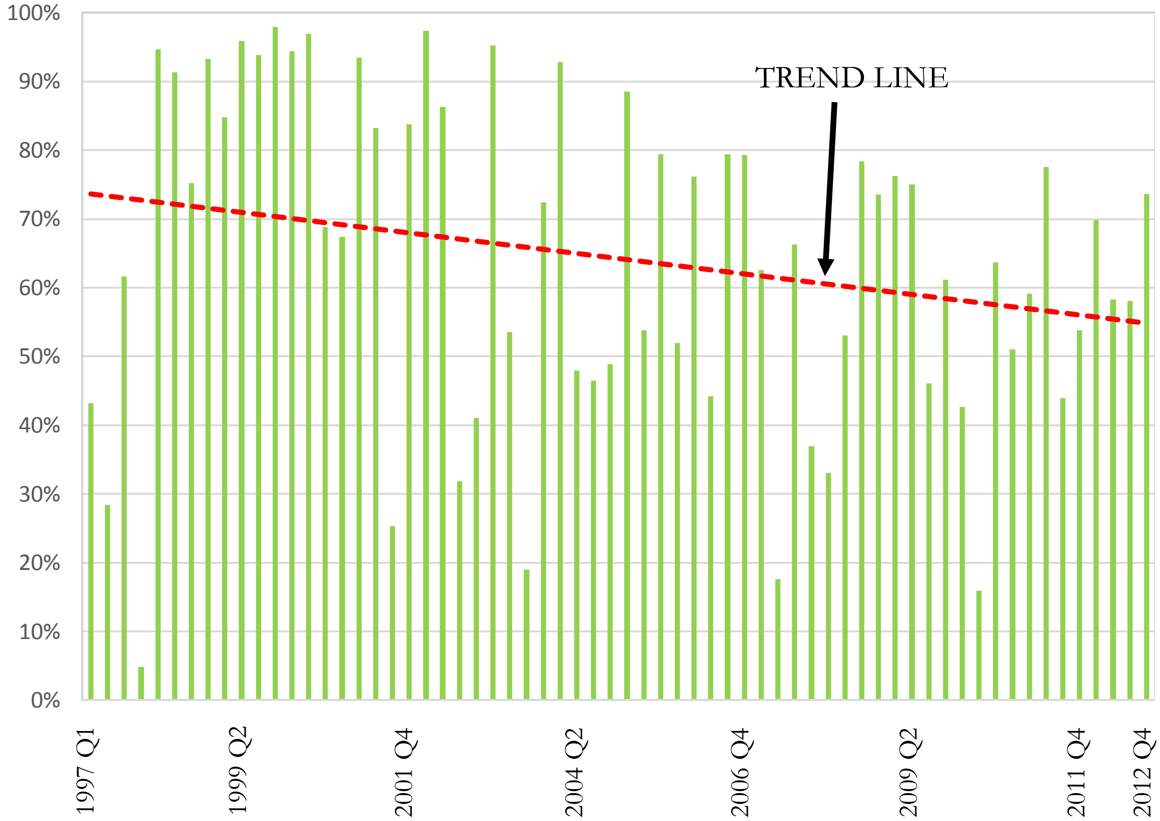
4.1. Introduction

The U.S. has been consistently one of the largest exporters of soybeans to the Philippines. From 1997 to 2012, U.S. quarterly soybean exports to the Philippines averaged close to 27 million kilograms. U.S. soybeans represented about 64 percent on average of all Philippine soybean imports during this period (Figure 4.1). Key soybean competitors to the U.S. are Canada and China, which captured 10 percent and 3 percent of the Philippine soybean import market shares on average, respectively, during the same time period.[19]

Market demand for soybeans is high in the Philippines. Soybean products such as soy sauce, soy milk and *tofu* (bean curd) are prominent in the Philippine diet. The Philippine market also uses other soy-based products such as livestock feed and soy ink. Because domestic Philippine soybean production has averaged less than 2,000 metric tons per year since 1999, according to the Food and Agriculture Organization of the United Nations, the Philippine market continues to be a significant soybean export destination. Although this can be encouraging to U.S. soybean exporters, the U.S. market share of soybean exports to the Philippines is in a downward trend, as shown in Figure 4.1. For the U.S. to remain competitive in the Philippine market, U.S. soybean exporters must identify and address the factors causing this decreasing market share trend.

[19] According to the Economic Research Service of the U.S. Department of Agriculture, despite being the world's biggest importer of soybeans, China is still the fourth leading soybean producer. (See http://www.ers.usda.gov/topics/crops/soybeans-oil-crops/trade.aspx, Accessed: May 7, 2015). Even though local soybean consumption has far exceeded production, China has consistently been exporting soybeans to the Philippines, capturing more than 40% market share at one quarter.

Figure 4.1. Share of Soybean Imports from U.S. to Total Soybean Imports, Philippines (First Quarter 1997 to Fourth Quarter 2012)



Source: Global Trade Atlas, *Global Trade Information Services*.

Competitiveness in the international soybean trade market is driven not only by soybean price but also by quality. As to which factor is relatively more important depends on the market's tendency to be either more sensitive to price or more sensitive to quality (Wilson and Gallagher, 1990).[20] Determining whether the Philippine soybean market is more sensitive to price or to quantity can help to explain the downward trend of U.S. soybean imports to the Philippines. This chapter will contribute to the explanation by analyzing data on import market share and prices of U.S. soybeans vis-à-vis those

[20] Wilson and Gallagher (1990) refers to the two categories as being "price-conscious" and "quality-conscious", respectively.

from three other import origins: Canada, China, and the Rest of the World (ROW). In particular, this chapter analyzes whether the downward trend in U.S. market share is due to inherent quality differences among soybeans from the three competing exporting countries or is attributed to relative price changes.

There is anecdotal evidence suggesting that price and quality are both drivers of soybean demand in the Philippines. According to a report by the Foreign Agricultural Service of the U.S. Department of Agriculture, Philippine consumers are generally considered very price sensitive (U.S. Department of Agriculture, 2009). As such, the downward trend in the demand for U.S. soybeans may have been due to relative price changes that favored U.S. competitors. However, the same report also noted that the Philippine market tends to prefer U.S. food products because of the prevalent perception among Philippine buyers that U.S.-based products are consistently of high quality. Essential to this is the idea that soybeans are heterogeneous-like goods. Single commodity products may be considered heterogeneous because of quality differences resulting from diversity in geographic and climatic factors, farmers' agronomic practices, and traders' marketing practices. These factors naturally vary across soybean exporting countries, which would result in differences in soybean quality. For instance, Grieshop and Fahey (2001) found that nutrient compositions vary among Brazilian, Chinese, and U.S. soybeans because of environmental conditions experienced where the soybeans grow. Crude protein, amino acid, and lipid concentrations varied depending on production location. Consequently, these differences may yield competitive advantages in international trade. In other words, these quality differences are perceived to have an impact on exporters' competitive behavior. As such, one hypothesis is that despite the prevalent perception of the Philippine market preferring the quality of U.S. soybeans, the decline in U.S. market share in the Philippine soybean import market may be linked to a gradual shift in preference toward quality inherent in soybeans sourced from U.S. competitors.

Determining whether relative import price changes or shifts in market preferences is a major cause of the declining U.S. soybean import market share in the Philippines is an empirical question that can be achieved by examining demand elasticities and measures of consumer preferences. These values can be estimated using a market share demand model proposed by Case (1974). Using a set of assumptions, Case derived a system of market share demand equations where parameters can be calculated indicating individuals' preferences for heterogeneous-like products. The system can likewise derive another parameter that estimates price responsiveness of market shares. The Case methodology can, therefore, indirectly measure individuals' relative preferences for heterogeneous-like products. I recognize upfront that the Case methodology has obvious theoretical weaknesses, but in the absence of historical quality attribute data and the absence of buyer preference information, the Case methodology provides the most reasonable approximate of preference trends and the best estimate of own- and cross-price elasticity estimates for evaluating import policies.[21]

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[21] Two closely related studies using alternative approaches that are worth noting are Koo et al. (2001) and Lakkakula et al. (2015), Koo et al. used a translog cost function approach to derive import elasticities and analyze import demand for wheat differentiated by class and country of origin in the Japanese wheat flour milling industry, while Lakkakula et al. analyzed changes in country shares of global rice exports using an econometric, shift-share analytical framework. See Tongeren et al. (2001) for an excellent review of alternative modelling approaches in the area of agricultural trade and policy.

4.2. Case Market Share Demand Model

The market share demand model used in this chapter was introduced by Case (1974) and further developed by Gallagher (1990), Gallagher et al. (1988), and Kohli and Morey (1990). The market share demand model builds on the basic economic theory that the probability of a supplier's product being chosen is based on the relative price difference between that supplier's product and competing suppliers' products. Thus, one critical assumption in this model is that products or goods are not perfect substitutes but are instead close substitutes, such that competitors are allowed to sell at different prices.

Consider a market of $i = 1,2, \dots, N$ competitors. The market share for product i, S_i, can be expressed as:

$$S_1(p_1, p_2, \dots, p_N) = \left[\left(\frac{m_i}{m_1} \times \frac{p_i}{p_1}\right)^{\alpha} + \left(\frac{m_i}{m_2} \times \frac{p_i}{p_2}\right)^{\alpha} + \cdots + \left(\frac{m_i}{m_N} \times \frac{p_i}{p_N}\right)^{\alpha}\right]^{-1} \tag{4.1}$$

where p_i is the price of the product i; m_i is a measure of consumer preference for the product i; and α measures the elasticity of substitution (i.e., the percentage change in relative market shares for a 1% change in relative prices). Relatively large values of α indicate that consumers adjust purchasing patterns quickly, while small values indicate slower purchase pattern adjustments. This also means that in a market with perfectly homogenous goods, suppliers will each have an equal market share and this is indicated by $\alpha = 0$. This model assumes that prices are exogenous and that buyers in the market make purchasing decisions based on relative prices. Thus, market shares depend only on the price ratios p_i/p_j.

Equation 4.1 is derived from a simplified logistic demand function proposed by Case (1974). It has the following properties:

i. $\sum_{i=1}^{N} S_i(p_1, p_2, p_3) = 1$

ii. $\lim_{p_i \to 0} S_i(p_1, p_2, \dots, p_N) = 1$ for fixed p_j and $i \neq j$

The first property simply states that the sum of all shares should equal to 1, while the second property reflects the standard effect of relative prices on market preference; hence, the market share of a good will increase as its price decreases.

Now, let $\beta_{ij} = m_i/m_j$, a measure of relative preferences. Equation 4.1 becomes:

$$S_1(p_1, p_2, \dots, p_N) = \left[\left(\beta_{i1} \times \frac{p_i}{p_1}\right)^{\alpha} + \left(\beta_{i2} \times \frac{p_i}{p_2}\right)^{\alpha} + \cdots + \left(\beta_{iN} \times \frac{p_i}{p_N}\right)^{\alpha}\right]^{-1} \tag{4.2}$$

The preference parameter, β_{ij}, captures the extent of consumer preference for good i over good j. For relatively homogenous goods, any differences in the preferences between i and j essentially reflects product differentiation between goods i and j. A market has a preference for good i compared to good j if:

$\beta_{ij} > 1 \quad for\ i \neq j$

On the other hand, the market has a preference for good j over good i if:

$\beta_{ij} < 1 \quad for\ i \neq j$

Competing goods are less differentiated when the preference parameter value moves closer to one, such that in the case of a perfectly homogenous product:

$\beta_{ij} = 1 \quad for\ i \neq j$

In terms of magnitude of preferences, relatively large values of β_{ij} indicate that consumers adjust to purchasing patterns quickly, while small values indicate slow purchase pattern adjustments.

By definition:

(4.3) $\beta_{ij} = 1 \quad for\ i = j$

(4.4) $\beta_{ij} = \dfrac{1}{\beta_{ji}}$

(4.5) $\beta_{ij} = \dfrac{\beta_{kj}}{\beta_{ki}} \quad for\ k \neq i\ and\ k \neq j$

Modifying Equation 4.2 to the case of a market with four competitors, the corresponding system of market demand share equations for relatively homogenous goods $i = 1, 2, 3, 4$ is:

(4.6)
$$S_1 = \left[1 + \left(\beta_{12} \times \frac{p_1}{p_2}\right)^{\alpha} + \left(\beta_{13} \times \frac{p_1}{p_3}\right)^{\alpha} + \left(\beta_{14} \times \frac{p_1}{p_4}\right)^{\alpha}\right]^{-1}$$

$$S_2 = \left[\left(\beta_{21} \times \frac{p_2}{p_1}\right)^{\alpha} + 1 + \left(\beta_{23} \times \frac{p_2}{p_3}\right)^{\alpha} + \left(\beta_{24} \times \frac{p_2}{p_4}\right)^{\alpha}\right]^{-1}$$

$$S_3 = \left[\left(\beta_{31} \times \frac{p_3}{p_1}\right)^{\alpha} + \left(\beta_{32} \times \frac{p_3}{p_2}\right)^{\alpha} + 1 + \left(\beta_{34} \times \frac{p_3}{p_4}\right)^{\alpha}\right]^{-1}$$

$$S_4 = \left[\left(\beta_{41} \times \frac{p_4}{p_1}\right)^{\alpha} + \left(\beta_{42} \times \frac{p_4}{p_2}\right)^{\alpha} + \left(\beta_{43} \times \frac{p_4}{p_3}\right)^{\alpha} + 1\right]^{-1}$$

Preferences and tastes are known to change over time. To incorporate structural shifts of preferences over time, I adopted the method in Wilson and Gallagher (1990) and modified the preference parameter, β_{ij}, to include a non-linear trend variable (T):

$$\beta_{ij} = \beta_{ij,t=1} \times T^{\delta_{ij}} \tag{4.7}$$

where $\beta_{ij,t=1}$ is the value of the preference parameter of product i over product j at the start of the sample period ($t = 1$), T is a time trend variable, and δ_{ij} captures the annual shift in the preference parameter from exogenous factors affecting the relative market share of product i relative to product j.

The time trend serves to capture the effects of other exogenous factors on consumer preferences, such as changes in per capita income, population, composition and purchasing behaviors of export demand markets, and processing technology among others. Incorporating structural changes in preferences over time, the system of market share demand equations then becomes:

$$\begin{aligned} S_1 &= \left[1 + \left(\beta_{12,t=1} \times T^{\delta_{12}} \times \frac{p_1}{p_2}\right)^{\alpha} + \left(\beta_{13,t=1} \times T^{\delta_{13}} \times \frac{p_1}{p_3}\right)^{\alpha} \right. \\ &\qquad \left. + \left(\beta_{14,t=1} \times T^{\delta_{14}} \times \frac{p_1}{p_4}\right)^{\alpha}\right]^{-1} \\ S_2 &= \left[\left(\beta_{21,t=1} \times T^{\delta_{21}} \times \frac{p_2}{p_1}\right)^{\alpha} + 1 + \left(\beta_{23,t=1} \times T^{\delta_{23}} \times \frac{p_2}{p_3}\right)^{\alpha} \right. \\ &\qquad \left. + \left(\beta_{24,t=1} \times T^{\delta_{24}} \times \frac{p_2}{p_4}\right)^{\alpha}\right]^{-1} \end{aligned} \tag{4.8}$$

$$S_3 = \left[\left(\beta_{31,t=1} \times T^{\delta_{31}} \times \frac{p_3}{p_1}\right)^{\alpha} + \left(\beta_{32,t=1} \times T^{\delta_{32}} \times \frac{p_3}{p_2}\right)^{\alpha} + 1 + \left(\beta_{34,t=1} \times T^{\delta_{34}} \times \frac{p_3}{p_4}\right)^{\alpha}\right]^{-1}$$

$$S_4 = \left[\left(\beta_{41,t=1} \times T^{\delta_{41}} \times \frac{p_4}{p_1}\right)^{\alpha} + \left(\beta_{42,t=1} \times T^{\delta_{32}} \times \frac{p_4}{p_2}\right)^{\alpha} + \left(\beta_{43,t=1} \times T^{\delta_{43}} \times \frac{p_4}{p_3}\right)^{\alpha} + 1\right]^{-1}$$

Finally, Equation 4.8 implies a log-linear form of the system of market demand share equations relative to one competitor (see Houck and Ryan, 1978). Using Equations 4.3, 4.4, and 4.5 as cross-equation parameter restrictions in the estimation and focusing only on the market demand shares of producer of product $i = 1$ relative to the market demand shares of producers of products $j = 2,\ 3, 4$, the equivalent system of $i - 1$ log-linear equations is:

$$(4.9) \quad \begin{aligned} ln\left(\frac{S_2}{S_1}\right) &= \alpha ln\left(\beta_{12,t=1}\right) + \alpha\delta_{12}\ ln(T) + \alpha\ ln\left(\frac{p_1}{p_2}\right) \\ ln\left(\frac{S_3}{S_1}\right) &= \alpha ln\left(\beta_{13,t=1}\right) + \alpha\delta_{13}\ ln(T) + \alpha\ ln\left(\frac{p_1}{p_3}\right) \\ ln\left(\frac{S_4}{S_1}\right) &= \alpha ln\left(\beta_{14,t=1}\right) + \alpha\delta_{14}\ ln(T) + \alpha\ ln\left(\frac{p_1}{p_4}\right) \end{aligned}$$

I applied this model to the case of the Philippine soybean import market to analyze the declining market share of U.S. imports to the Philippines. Specifically, the market share of U.S. ($i = 1$) is examined relative to the markets shares of Canada ($j =$

2), China ($j = 3$), and ROW ($i = 4$). The elasticity of substitution (α), the measure of preferences for product 1 over product j ($\beta_{1j,t=1}$), and the measure of shifts in preferences over time (δ_{1i}) are the parameters to be estimated in this system of equations.

4.3. Calculating Demand Elasticities and Preference Parameters

The results from estimating Equation 4.9 can be used to derive elasticities and preference parameters. To derive the import demand elasticities, let X_i be the quantity of imports from country i. By definition, in an import market with three players:

$$X_i = S_i \times \sum_{i=1}^{3} X_i$$

A price change's effects on import quantities can be evaluated by differentiating and applying the Chain Rule:

$$\text{(4.10)} \quad \frac{\Delta X_i}{\Delta p_j} = \sum_{i=1}^{3} X_i \times \left(\frac{\Delta S_i}{\Delta p_j}\right) + S_i \times \left(\frac{\Delta \sum_{i=1}^{3} X_i}{\Delta p_j}\right)$$

The model assumes that (i) multiple export demand markets offer non-differentiated products and (ii) no exporting country has a large enough share of the importing country's market to affect the total export quantity. This means that if relative prices change such that demand will move from one commodity to another, only relative market shares change; total demand remains the same. As such, changes in any one commodity price will not affect the market size (i.e., Philippine buyers will procure soybeans from somewhere around the global at a similar price); the market size effect $\Delta \sum X_i / \Delta p_j$ is zero. Therefore, Equation 4.10 is reduced to:

$$(4.11) \qquad \frac{\Delta X_i}{\Delta p_j} = \sum_{i=1}^{3} X_i \times \left(\frac{\Delta S_i}{\Delta p_j}\right)$$

The price elasticity from the market demand share functions ($E_{S_i p_j}$) estimated from Equation 4.9 should be identical to the import demand price elasticity ($E_{X_i p_j}$). Accordingly, import demand own-price elasticity is expressed as:

$$(4.12) \qquad E_{X_i p_i} = E_{S_i p_i} = -\alpha(1 - S_i)$$

whereas the corresponding import demand cross-price elasticity is expressed as:

$$(4.13) \qquad E_{X_i p_j} = E_{S_i p_j} = \alpha S_i \quad for\ i \neq j$$

Based on Equations 4.12 and 4.13, the own-price and cross-price import demand elasticities are bound by the elasticity of substitution (α). In addition, comparative statics show that the own-price import demand elasticity is an increasing function of market share and a decreasing function of the elasticity of substitution:

$$\frac{\partial E_{S_i p_i}}{\partial S} = \alpha > 0$$

$$\frac{\partial E_{S_i p_i}}{\partial \alpha} = -(1 - S_i) < 0 \quad since\ 1 > S_i$$

4.4. Data and Estimation Method

Philippine data on soybean import quantities (in bulk, total) from all countries including Canada, China, and the U.S. and their corresponding prices were obtained from the Global Trade Atlas (GTA) database of the Global Trade Information Services (2013). As is expected, empirical data on quarterly average soybean prices are not available. The GTA dataset, however, has complete information on total value of imports per country of origin. Unit values of soybeans are thus calculated (total value of imports divided by import quantities) and used as proxy for soybean prices. There should be caution, however, in the use of unit-values as proxies for prices. Their use have been known to result in biased estimates, especially to measurement error. Given that price export and import price data are rarely available, there is no known solution to the problem of using unit-values, except that the reader be aware and provide caution in interpreting the results (see Nicita and Olarreaga, 2007).

The analysis covers quarterly time series data for the 16-year period from January 1997 to December 2012. While Argentina and Brazil have recently become major soybean importers in the Philippines, their data is not sufficient to generate meaningful results. Therefore, these two countries are grouped under the Rest of the World (ROW) category.[22]

[22] Of the total 64 quarterly data points from 1997 to 2012, Argentina only has 54.7% observations while Brazil has 29.7%. Canada, China, and U.S. has all 100%.

Table 4.1 provides summary statistics of prices, quantity, and market share data of import origins used in the analysis. Looking at average market shares, imports from the U.S. dominate the Philippines soybean import market.

Table 4.1. Summary Statistics of Philippine Import Quantities and Prices by Origin (First Quarter 1997 to Fourth Quarter 2012)

Origin	Average	Standard Deviation	Minimum	Maximum
Unit Value (U.S. dollars per kilogram)				
United States	0.33	0.11	0.16	0.61
Canada	0.33	0.11	0.17	0.70
China	0.41	0.31	0.11	2.67
ROW	0.31	0.14	0.06	0.59
Quantity (in thousands kilograms)				
United States	27,109.50	25,142.41	645.65	89,113.50
Canada	2,416.54	3,406.40	494.56	26,956.68
China	811.84	1,416.23	24.05	6,988.14
ROW	10,892.21	19,419.54	5.298	95,237.04
Market Shares (percentage)				
United States	64.24	23.68	4.88	97.92
Canada	10.10	9.80	0.77	43.02
China	3.05	4.44	0.23	20.35
ROW	22.61	22.88	0.05	89.16

Notes:

1. Number of Observations: 64
2. For the market shares, we assume the market consists of imports from only the United States, Canada, China, and Rest of the World (ROW).
3. Unit-values (total value of imports divided by import quantity) is used as proxy for prices.

Equation 4.9 is a system of time series equations that are log-linear in the parameters and have cross-equation relationships among parameters and error terms. As such, seemingly related regression (Zellner, 1962; Zellner and Huang, 1962; Zellner, 1963) by the iterative feasible generalized nonlinear least squares method is used to estimate the parameters. Estimation using this method yields unbiased and more efficient parameter estimates in the presence of cross-equation serial correlation (Greene, 1993).

4.5. Estimation Results

Table 4.2 summarizes parameter estimates of Equation 4.9. Except for the U.S. shift in trend coefficients relative to China's and ROW's, the regression coefficients are significantly different from zero.

The coefficient of the log of the price ratio (α), which reflects the sensitivity of market shares to changes in relative prices, shows a value of 0.66. An interpretation of this is that, on the average, a 1% increase in U.S. soybeans' relative price caused the relative market demand share from either Canada, China, or ROW to increase by 0.66%. This is a relatively low value, indicating less substitutability between U.S. soybeans and soybeans from the other three origins. This low price responsiveness may imply greater preference rigidity and reflects a market that is relatively more quality-conscious. Because the relative demand share increase is less than the increase in price (0.66% < 1%), this implies that Philippine soybean buyers are less likely to shift demand from U.S. soybeans to Chinese or Canadian soybeans when faced with increases in U.S. prices. This supports empirical data which indicates the U.S. capturing the biggest share of the Philippine soybean import market for the majority of the years between 1997 and 2012 (despite having a downward trend in market share).

Given that the data is quarterly running from the first quarter of 1997 to the fourth quarter of 2012, the last value of the trend variable (T) is 64. As such, to calculate the value of the preference parameter at the end of the estimation period, the following formula is used, which is derived from Equations 4.7:

$$\beta_{1j,t=64} = \beta_{1j,t=1} \times 64^{\delta_{ij}}$$

Table 4.2. Parameter Estimates for Soybean Exports to the Philippines (First Quarter 1997 to Fourth Quarter 2012)

	Equation, Dependent Variable: $ln\left(\frac{S_j}{S_{USA}}\right)$		
Parameters	$ln\left(\frac{S_{CANADA}}{S_{USA}}\right)$	$ln\left(\frac{S_{CHINA}}{S_{USA}}\right)$	$ln\left(\frac{S_{ROW}}{S_{USA}}\right)$
α	0.6613 *** (0.2462)	0.6613 *** (0.2462)	0.6613 *** (0.2462)
$\beta_{12,t=1}$	–5.2437 ** (2.1063)		
δ_{12}	0.5906 * (0.3280)		
$\beta_{13,t=1}$		–5.8326 ** (2.4338)	
δ_{13}		0.1664 (0.2623)	
$\beta_{14,t=1}$			–5.0647 * (2.5969)
δ_{14}			0.5470 (0.5674)
Model Fit (χ^2)	12.77 ***	7.94 **	8.86 **

Notes:
1. Number of observations: 64.
2. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.
3. Standard errors are in parentheses.
4. Subscript assignments: United States (1), Canada (2), China (3) and ROW (4).

Recall that the value of the preference parameter, β_{ij}, and the extent of its deviation from the value of 1 indicate a preference for soybeans from one source country relative to those from the other two countries. The results presented in Table 4.3 show that the preference parameters for U.S. soybeans relative to soybeans from Canada, China, and the ROW are significantly less than 1, which indicates a very strong market preference for U.S. soybeans. Wilson and Gallagher (1990), however, caution against interpreting extreme values of β_{ij}. Extreme values may indicate either very little price response or may be due to exceedingly large or exceedingly small shares. Nevertheless, these extreme values are still an indicator of strong preference for U.S. soybeans by

Philippine buyers. Tremendous changes in relative prices must occur before any significant changes in relative market shares will occur. These results are consistent with the estimated low elasticity of substitution value, α, which itself indicates low price responsiveness of the Philippine buyers to relative price changes. We can interpret this as buyers responding less to any change in relative prices because they strongly prefer soybeans from one origin (US).

Table 4.3. Complete Preference Parameter Estimates (United States, Canada, China, and Rest of the World Soybean Exports to the Philippines)

	First Quarter 1997				Fourth Quarter 2012			
Country	USA	Canada	China	ROW	USA	Canada	China	ROW
USA	–	0.0053	0.0029	0.0063	–	0.0616	0.0059	0.0614
Canada	189.36	–	0.5549	1.1960	16.24	–	0.0951	0.9978
China	341.26	1.8022	–	2.1554	170.83	10.5186	–	10.4594
ROW	158.33	0.8361	0.4639	–	16.28	1.0022	0.0953	–

Notes: The preference parameters represent the level of product differentiation between two goods. They are price premiums or discounts, relative to imports from United States that would provide each good equal market share. For each period's preference parameter matrix, the upper-right values represent the reciprocal of the values from the lower-left values.

Although U.S. soybeans were consistently preferred during the 16-year time period, Table 4.3 also shows the value of the preference parameter for the U.S. relative to all three of the other import origins, which increased between the first quarter of 1997 and fourth quarter of 2012. This indicates that the preference for U.S. soybeans by Philippine buyers has decreased relative to the preference for soybeans from Canada, China, and ROW. While the declining prices of Canadian soybeans might be a factor in this shift of preference away from U.S. soybeans, previous results of low relative price responsiveness of the Philippine market (α) makes it less likely that the decline in the preference for U.S. soybeans was due to any decline in prices (or unit values) of soybeans from other import origins. Instead, it more likely implies that the Philippine market is increasingly developing a preference for one or more non-price factors (or quality traits) inherent in imported soybeans.

Table 4.4 presents own-price import demand elasticities and cross-price import demand elasticities, both computed at the mean. These elasticities are derived from reported coefficients in Table 4.2 and calculated using Equations 4.12 and 4.13.

Table 4.4. Demand Elasticities for United States, Canada, and China Soybean Exports to the Philippines

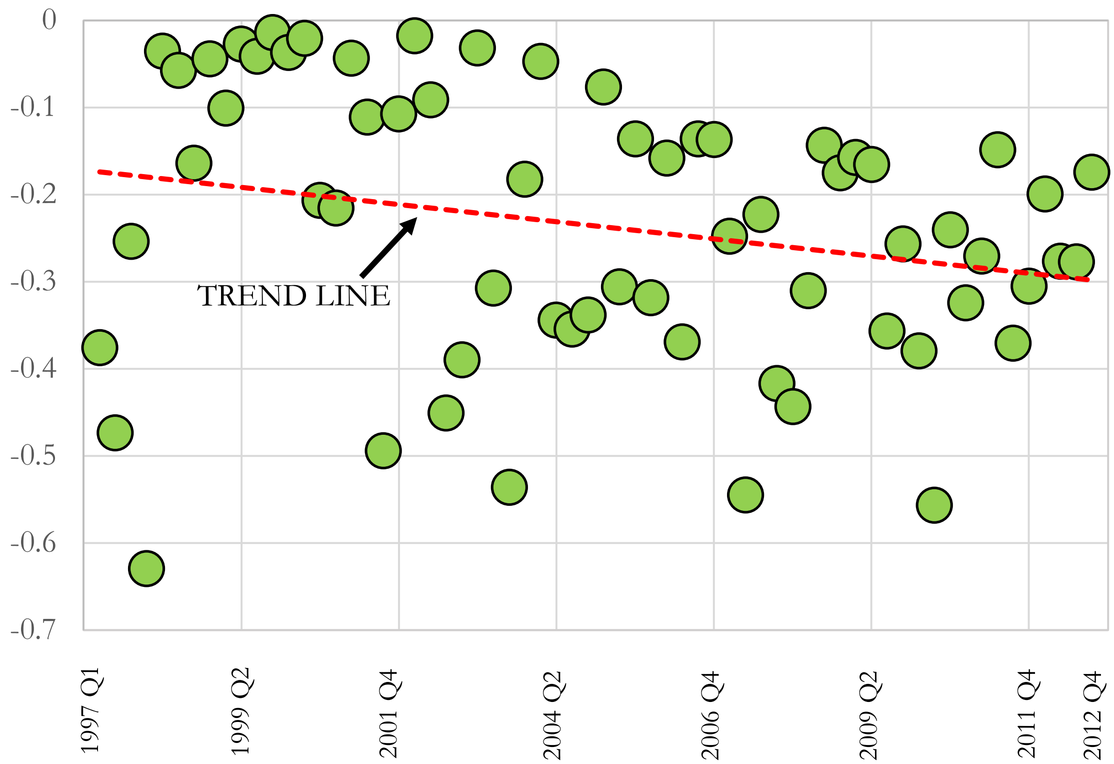
Country/Timeframe	Elasticity of Demand at Share Mean	
	Own-Price	Cross-Price *
United States	– 0.2365	0.4248
Canada	– 0.5945	0.0668
China	– 0.6411	0.0202
ROW	– 0.5118	0.1495

Note: * - Cross-price elasticities refer to the percentage change in the quantities of soybeans imported from other countries for a 1% change in the price of the indicated country source.

The import demand elasticities support the previous result of Philippine market's preference for U.S. soybeans. Soybeans from Canada, China, and ROW are relatively more elastic that those from the U.S. (–0.59, –0.64, and –0.51, respectively, versus the U.S.'s – 0.24). Thus, even if U.S. soybean prices increase, current buyers of U.S. soybeans are relatively less likely to shift to soybeans from other import origins. On the other hand, if prices of soybeans from Canada, China, or ROW increase, buyers are relatively more likely to shift their purchases.

Consistent with results in Table 4.3, point price elasticity estimates of import demand for U.S. soybeans are increasing in absolute value over time (see Figure 4.2).

Figure 4.2. Import Demand Point Elasticity Estimates over Time for U.S. Soybean Exports to the Philippines (First Quarter 1997 to Fourth Quarter 2012)



This means that the Philippine market has become more and more sensitive to changes in the prices of U.S. soybeans. Given that price elasticity of soybeans from Canada, China, and ROW is relatively stable, this increasing trend (in absolute values) of price elasticity for U.S. soybeans would mean that the sensitivity Philippine market to U.S. soybean prices will eventually be equivalent to the market's sensitivity to prices of soybeans from Canada, China, and the ROW. In other words, the perception by Philippine buyers that soybeans from U.S. are of superior quality eventually may not be enough to keep U.S. as the leader in the Philippine soybean import market.

4.6. Concluding Remarks

The low price response parameter and consistently high preference parameter for U.S. soybeans imply that the Philippines market is quality-conscious and that there is high preference for U.S. soybeans. The market is characterized by a strong preference for certain soybean qualities found in U.S. soybeans, such that any changes in relative prices of soybeans imported from different countries have minimal effect on demand for U.S. soybeans. This does not imply that the U.S. has better quality soybeans than those from Canada, China, or other country of origin. Instead, it suggests that Philippine buyers have rigid preferences for the quality provided by U.S. soybeans. The elasticity of substitution test results indicate that Philippine soybean purchasers are less likely to shift demand from U.S. soybeans to soybeans from Canada, China, or ROW when faced with increased U.S. soybean prices. The estimated preference pattern communicates similar strong Philippine preferences for U.S. soybeans. Import demand elasticities further indicate the Philippine market's preference for U.S. soybeans. However, changes over time in the preference parameters and elasticities suggest that the Philippine market might eventually approach sensitivity to U.S. soybean prices equivalent to its sensitivity to prices of soybeans from Canada, China, or ROW. On the other hand, note that when elasticities eventually did become similar, the values were still relatively low. This indicates that the Philippine market is still, by and large, a quality-conscious market. In order to stop the declining trend in the share of U.S. soybeans in the Philippine import market, the U.S. soybean industry will have to increase investment in innovating soybean quality traits.

Several limitations of this chapter are worth noting. First, the analysis in this chapter assumes that source of origin is important in determining export competitiveness.

The specific reasons why differences exist, however, is not explored in detail. In particular, what soybean qualities seem to give the U.S. is a competitive advantage over Canada, China, and the rest of the world. In addition, the estimation results indicate that preferences for U.S. soybeans have decreased over time. Given that there is no evidence that this shift is due to changes in relative prices, it can be inferred from the results that the change is due to the increasing preference of the Philippine market for qualities inherent in soybeans from other import origins. So what are the qualities in soybeans from other competitors that have caused the Philippine market to slowly shift away from U.S. soybeans over time? Second, another limitation of this chapter is the exclusion of major importers, such as Argentina and Brazil, as a separate category due to data issues. It would be interesting to see if the decrease in preference for U.S. soybeans occurs at the same time that preferences for Argentine or Brazilian soybeans are increasing.

Third, this chapter only analyzes total soybean imports in bulk to the Philippines. It would be interesting to assess the results at a disaggregated level. Specifically, it would be good to assess whether or not the performances of intermediate products of soybeans—soybean meal and soybean oil—can be examined to see if the results presented in this chapter still hold. Finally, another shortcoming of this chapter is that the Case market share demand model assumes constant elasticity of substitution between each pair of competing sources of imported soybeans (i.e., between U.S. and Canadian soybeans, between U.S. and Chinese soybeans, and between Canadian and Chinese soybeans). This is a very restrictive assumption imposed on the Philippine demand for soybean imports. Relaxing this assumption would lead to a richer analysis by allowing the Philippine market to adjust to relative price changes in each of the competing soybean import sources.

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VITA

Jewelwayne Cain was born to a family of coconut farmers in the southern part of the Philippines. He graduated with a Bachelor's degree in Business Economics from the University of the Philippines and worked for non-profit organizations as a policy researcher and program coordinator after earning his undergraduate degree. Enamored by applied economics, he decided to earn his Master's degree in Development Economics from the University of the Philippines while serving as a teaching assistant. He then spent almost four years as an Economics and Statistical analyst at the Economic Research Department of the Asian Development Bank (ADB). At ADB, Wayne co-authored several published articles and book chapters on poverty and inequality. Throughout this period, he focused on honing his skillset in statistical programming and analysis of household level panel data. His experience as a teaching assistant as well as interaction with some of the leading academicians in the Philippines inspired him to think about building a career in the academe. He earned his M.A. in Economics from University of Missouri-Columbia in 2012 and proceeded to continue with his Ph.D. in Agricultural and Applied Economics. During his graduate program, he co-taught several economic courses and received several awards as a graduate teaching assistant. He also spent a summer serving as an Adjunct Faculty at the Central Methodist University and Columbia College in the area. A family opportunity to relocate to Florida allowed him to take on an Adjunct Faculty position at the University of Tampa Sykes College of Business and the University of South Florida-St. Petersburg Kate Tiedemann College of Business while concurrently finishing his dissertation. He accepted a full-year Visiting Instructor of Economics at the Sykes College of Business for the school year 2015-2016.