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Are Ethanol Policies Affecting Crop Prices? An Empirical Analysis of US Ethanol Policies

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List of Acronyms

BEA – Bureau of Economic Analysis

CPI – Consumer Price Index

CRP – Conservation Reserve Program

DDG – Dried Distillerss Grain

DOE – United States Department of Energy

E85 – Fuel containing 85% ethanol

EIA – Energy Information Administration

EPA – United States Environmental Protection Agency

FAPRI – Food and Agricultural Policy Research Institute

FCPI – Farm Crop Price Index

GDP – Gross Domestic Product

GHG – Green House Gas

MTBE – Methyl Tertiary Butyl Ether

NASS – National Agricultural Statistics Service

OLS – Ordinary Least Squares

RFA – Renewable Fuels Association

RFS – Renewable Fuel Standard

US DOE – United States Department of Energy

USDA – United States Department of Agriculture

VEETC – Volumetric Ethanol Excise Tax Credit

1. Introduction

Ethanol is an energy source classified as a biofuel and it has been adopted by the United States as the protector of energy security and savior of the environment. It has been chosen as an alternative to gasoline because it can be mass produced with U.S. grown products, while emitting a lower concentration of Green House Gases (GHG) when consumed. The benefits of ethanol make the product seem too good to be true; however, there are many costs associated with ethanol as well. The most devastating cost being the influence on crop prices, which is often overlooked by policy makers and consumers. Since corn is the main input for U.S. ethanol production, over the last decade the rise in ethanol production has led to rising crop and food prices through indirect and substitution effects (Runge and Senauer, 2007). The lack of forethought by U.S. policy makers has lead to the promotion of ethanol as a quick fix for energy security and the environment. The history of ethanol in the United States shows that the ethanol market is not self-propelled and it is dependant on federal regulations to survive.

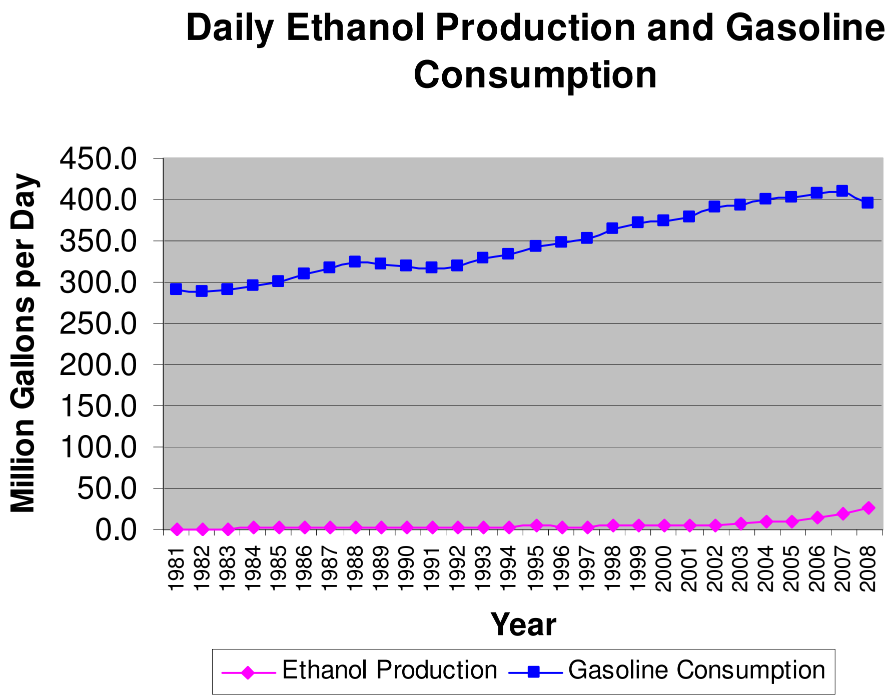
The market for ethanol in the United States started in the late 1970s. Fuel prices were skyrocketing as the oil supply in the U.S. was plummeting. The oil crises catalyzed energy security policies, and the government adopted ethanol as the most feasible solution. To promote the growth of the ethanol industry, and ultimately eliminate the reliance on foreign energy sources, the U.S. implemented a blenders' tax credit for ethanol (Gardner, 2007). However, historical ethanol production shows the policy was insufficient in its ability to promote the ethanol industry.

Environmental concerns also propelled the ethanol market in the 1970s. Additives had been used in refined gasoline since the 1950s to increase the oxygen content and improve the efficiency of engines. In the early 1970s, the preferred lead-based additive products were found to cause cancer through the saturation of drinking water. Therefore, the gasoline additive market contracted to two products: ethanol and Methyl Tertiary Butyl Ether (MTBE). Eventually ethanol was labeled as the less preferable additive, and MTBE was selected as the primary oxygenate by most blenders (EPA, 2008). Soon the United States' oil supply returned to the normal state and people abandoned ethanol. In the 1980's, the poorly developed credit policy, suppressed environmental concerns, and declining gas prices left the ethanol industry's supply and demand crippled.

Through the 1990s, the development of the ethanol market was unimpressive. Ethanol production in the U.S. grew from .9 billion gallons in 1990 to roughly 1.5 billion gallons in 1999 (RFA, 2009a). Most of the growth throughout the decade can be accredited to the Clean Air Act Amendments of 1990. The Amendments required oxygenates to be added to fuels in high pollutant areas to lower carbon monoxide emissions (Miranowski, 2007). Although, MTBE was simultaneously strengthening its foothold as additive of choice. The 63 percent increase in production over the decade might seem substantial, but it is insignificant when compared to the .36 billion gallons of gasoline Americans consumed *daily* in 1999, as shown in Figure 1 (EIA, 2009).

It was not until the new millennium that the United States reconsidered ethanol as a substitute for gasoline. The same pro-ethanol arguments used in the 1970s were also the vehicle behind the ethanol boom in the 2000s. September 11th created an unconditional demand for national security in the United States. Policy makers and citizens began to scrutinize America's vulnerabilities. Since over 60 percent of the country's oil was imported, the government highlighted energy security as an obvious chink in the United States' armor. Oil cartels, such as OPEC, presented considerable risk to the U.S. economy, which could be brought to a stand still

Figure 1 – U.S. Ethanol Production and Gas Consumption, 1981-2008



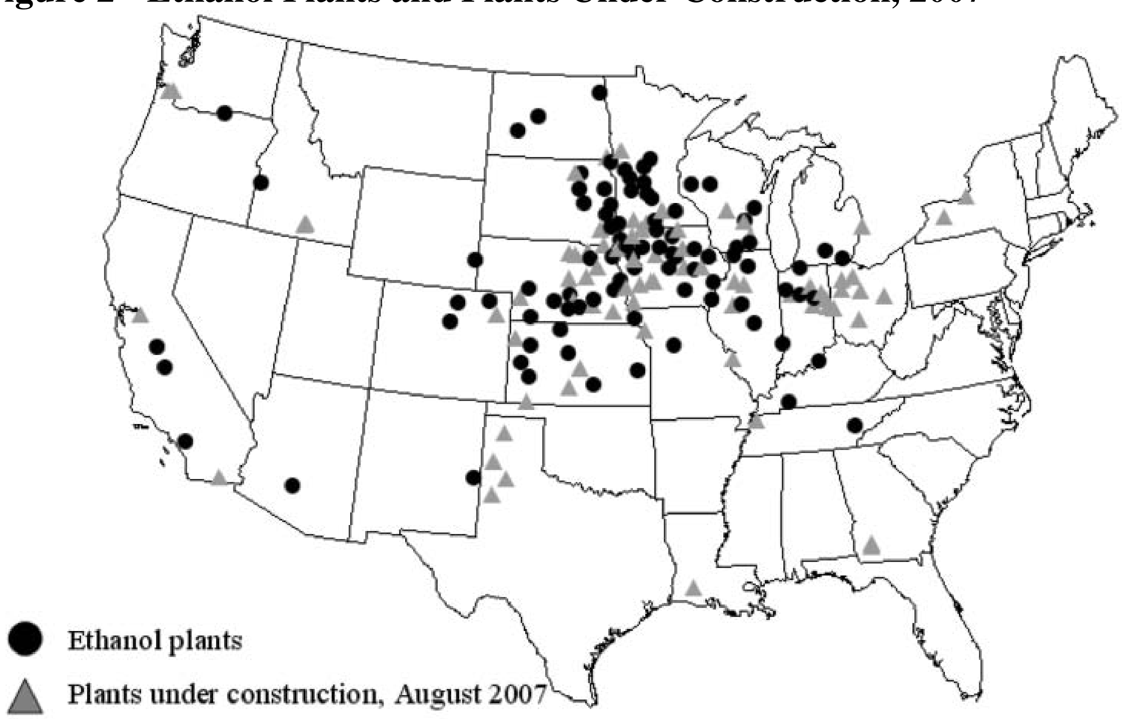
Source: EIA 2008 Annual Energy Review Table 10.3 and EIA 2009

with an oil supply shock (Miranowski, 2007). Once again, policy makers turned to ethanol as the solution. As the leading corn producer in the world, the United States had the potential to generate a considerable amount of ethanol that would have direct impacts on oil imports.

The demand for energy security complemented the surging demand for improved environmental quality in the 2000s. Media outlets began reporting scientists concerns about global warming to the American people, presenting GHG as the most widely accepted sources of global warming. The link between GHG and refined gasoline sparked a demand for a cleaner fuel substitute in the U.S. (Schneider and McCarl, 2001). As a result, the fuel market shifted towards ethanol as the alternate fuel of choice because of its environmental benefits when blended with gasoline or used as a replacement.

Energy security and environmental concerns are just two of the many reasons behind the increase in ethanol production and consumption in the 2000s. Like all markets, profits and regulations are the deciding factors of production in the ethanol industry. The turn of the century had a favorable mix of low corn prices, high gas prices, technological improvements, and lucrative policy bundles, which combined to make ethanol profitable. Consequently, ethanol plants began to spring up in grain growing states, as shown in Figure 2. The new facilities increased U.S. ethanol production to 9 billion gallons in 2008, and even more plants have been scheduled for construction (RFA, 2009a). Still, the enlarging market only represents a minute portion of total fuel consumption, see Figure 1. If, however, market conditions stay favorable, technology improves, and supporting policies stay intact, ethanol could become a sizeable competitor against gasoline in the near future.

Figure 2 - Ethanol Plants and Plants Under Construction, 2007



Source: Low and Isserman 2009

The benefit of being completely non-reliant on foreign energy is immeasurable. Unfortunately, the ethanol potential of our country is not large enough to eliminate our oil dependency; therefore, the energy security benefits of ethanol are limited. The environmental benefits of ethanol are limited as well. It is true that ethanol has lower carbon dioxide emissions than gasoline, but the use of ethanol will increase nitrogen oxide emissions (another harmful gas emission). The actual net environmental impact from using ethanol as a substitute to gasoline is actually closer to neutral than is commonly reported (Hahn and Cecot, 2008). These benefits would be worth the government intervention if the costs of the policies were small. Regrettably, the costs are not. The legislation has created billions of dollars in annual government spending along with creating inefficiencies in the fuel and crop markets.

The loss in social welfare that crop markets experience is a consequence of the relationship between rising ethanol production and rising crop prices. The question that arises is what percentage of the rising United States' crop prices are ethanol and the associated policies responsible for? Current literature on ethanol attempts to answer a similar question. A common theme amongst papers is the use of simulation models and focus on the long-run projections for determining the effects of ethanol production. The downsides of these studies are the simplifying assumptions the authors must make. Even with sensitivity analysis, the results in these papers could misrepresent ethanol's actual effects on crop prices if one or more of their short-run assumptions prove to be wrong. Using existing literature as a foundation, this paper will attempt to estimate the effects of the ethanol tariff, tax credit, consumption quota, and state-wide MTBE bans on crop prices. Specifically, the effects will be tested using a hedonic price model for corn, wheat, and soybean prices as a function of ethanol policies. Theory states that through indirect effects in the corn market and substitution effects in the wheat and soybean markets, the prices of all three commodities should rise as a result of ethanol policies. The investigation of the size of the effects on prices from the existing policies is conducted using crop and policy data collected from the United States Department of Agriculture (USDA) and the Renewable Fuels Association (RFA).

The next section of this paper describes the history of United States' ethanol policies as well as explains the theory behind ethanol policies' influence on crop prices. The third section reviews the previous literature on this topic. The fourth section presents the data and explains how the variables are generated. The fifth section walks through the evolution of the model and illustrates the methodology used. The sixth section reports the results of the regressions. The seventh, and final, section contains conclusions and discussions of the results.

2. Theory

2.1 Ethanol Policies

The United States government creates policies as solutions to problems, not to bolster the production of commodities, yet sometimes they are interrelated. Legislation surrounding the ethanol market is one such case. Improving the energy security and environment through the increased production and consumption of ethanol was the goal of implementing policies. Unfortunately, there are contradictions built into some of the ethanol legislation. The first example is the ethanol tariff. The United States implemented a \$.54 tariff on all imported ethanol beginning in 1980. The exception to this rule is countries involved in the Caribbean Initiative can export ethanol up to 7 percent of the United States' previous year's consumption without the tariff (Eidman, 2007). This policy is designed to protect U.S. ethanol producers from outside sources such as Brazil. Ultimately, the tariff's goal is to create energy security through a closed market, but it simultaneously contradicts the environmental rational behind using ethanol. Theoretically, with a tariff in place, U.S. ethanol prices will be higher than world prices causing consumption to fall below the optimal level. In 2004, the government decided deflated consumption was unacceptable, and developed a policy that would help lower ethanol prices.

The positive externalities related to ethanol, e.g., energy security and environmental improvement, needed to be realized through higher consumption for policies to be considered effective. The resulting policy was the Volumetric Ethanol Excise Tax Credit (VEETC), which acted as a $.51 subsidy for every gallon of ethanol blended with gasoline. The VEETC was part of the Americans Job Creation Act of 2004 and went into effect on January 1st, 2005 (Low an Isserman, 2009).[1] The policy revamped an outdated ethanol price support that was only available to blenders for specific levels of ethanol concentration. The new policy was much more beneficial for blenders, who were now allowed to mix in as much or as little ethanol as desired (RFA, 2009b). Blenders took advantage of the subsidy, and increased the demand for ethanol to levels the U.S. had never experienced before. The tax credit was designed to theoretically eliminate deadweight loss associated with unrealized marginal social benefits, as well as lessen the negative impact of the ethanol tariff on social welfare, yet it was still not enough to make ethanol a major competitor in the fuel industry.

Congress was not pleased with the ethanol consumption in the United States as a result of the tariff and VEETC. The production capacity was growing at faster rate than ethanol demand, and older, less-efficient ethanol plants stop operating. The government's solution was to mandate a consumption quota. The Renewable Fuels Standard (RFS) was part of the U.S. Energy Policy Act of 2005, and it ordered 4 billion gallons of ethanol to be sold as a final good each year in the

[1] The 2008 Farm Bill lowered the VEETC to $.45 per gallon of blended ethanol. The new policy was implemented in January, 2009.

U.S. starting in January, 2006. The quota was set to increase on an annual basis until it reached 7.5 billion gallons in 2012 (Rajagopal and Zilberman, 2007). The RFS was later updated in 2007 in the Energy Independence and Security Act. The new mandate increased all annual consumption quotas, and extended the duration of the RFS to 2022 (Low and Isserman, 2009).

The RFS created a synthetic demand for ethanol that would not have existed otherwise. Along with the VEETC, the RFS tried to capture the positive externalities of ethanol that the private markets would not realize. A few years after its adoption, the RFS proved to be a contradictory policy to the tariff. The consumption quota was the goal U.S. ethanol producers strived to reach each year, but they were limited by technology and profitability. Since the RFS was not a production quota, when the output of U.S. ethanol did not reach the desired level, the difference was imported from other countries. The number of gallons imported annually is only in the hundreds of millions, but the policy conflict is a good indication of the shortsightedness of the U.S. government's ethanol legislation.

The federal policies have focused on correcting national energy security rather than the environment. There is an argument that the government had the environment in mind when developing ethanol policies, but the environmental benefits are only a byproduct of its mission for energy security. The tariff is a blatant protectionist policy, while the VEETC and RFS inflate demand and indirectly cause producers to increase output; thus, eliminating some reliance on foreign energy. Without the distraction of national security, state governments have the ability to establish ethanol regulations solely for the sake of the environment's wellbeing.

At the turn of the century, MTBE was still the main oxygenate used in reformulated gasoline to comply with the Clean Air Act Amendments of 1990. Only in the Midwest—where ethanol production was the greatest—was MTBE second to ethanol. However, in the early years of the 2000s, the oxygenate additive market began to make a dramatic shift towards ethanol (Low and Isserman, 2009). The transition started with the discovery of MTBE residue on the surface of standing water in California. The Californian government applied to Congress for exemption from the Clean Air Act, but was denied. With no other options left, California called for a ban on MTBE by 2003, leaving ethanol as the best option as an additive.[2] By 2008, 24 states banned or restricted MTBE as an additive for gasoline (EPA, 2008). The state governments acted for the environment and the safety of the people, which helped ethanol capture a market that was previously impenetrable.

2.2 Ethanol Production's Impact on Crops[3]

The United States' ethanol production process uses a dry milling practice, similar to producing alcohol, with corn as the main input. First, the corn is ground into a meal and mixed with water to create a mash. Enzymes are then added to break the mash into simple sugars. Last, yeast is added to the simple sugars, and the mixture is allowed to ferment (RFA, 2009c). Dry milling creates two outputs: ethanol and dried distillers' grain (DDG), which can be sold in the feed market. The yields of this process are roughly 2.67 gallons of ethanol and 17.5 pounds of DDG per bushel of corn, which are ten percent higher than the yields a decade ago (Gallagher, Shapouri, and Brubaker, 2007). Even though the United States' ethanol technology is improving, it is inefficient compared to the rest of the world.

The major flaw with U.S. ethanol production is the use of a suboptimal input. A common way to measure the efficiency of energy products is the net energy balance—a ratio of energy the product yields versus the amount of energy it takes to produce. When compared with alternative inputs for ethanol, such as sugar cane used in Brazil, corn is found to have up to an eight times

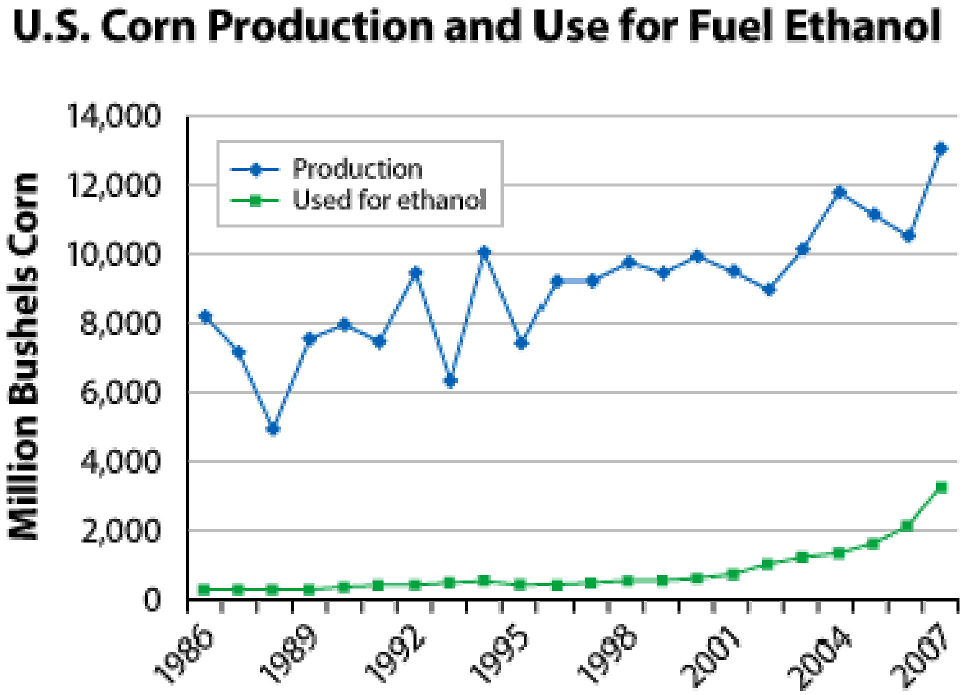
[2] California delayed the complete ban on MTBE to January, 2004.
[3] See Appendix 1 for theory graphs

lower net energy balance (Surowiecki, 2006). Why does the U.S. government promote an inefficient alternate fuel that is supposed to save the environment? The answer is simple: it is the best they have. By importing a sufficient supply of sugar or efficiently produced ethanol, the U.S. would be sacrificing energy security, which is the foundation upon which federal ethanol policies were built. Another alternative known as cellulosic biofuel—a biomass's cell membrane is broken into cellulose—has a greater net energy balance, but is not yet cost effective (RFA, 2009d).

Ethanol policies have facilitated the growth of the suboptimal ethanol production processes in the United States. Increasing demand and increasing supplier profits are causing ethanol production in the U.S. to grow, and corn production will have to adapt as the only cost-effective input option, see Figure 3. Traditionally, corn demand consisted of food, feed, and exports. Through improving technology, favorable weather conditions, and copious amounts of land, the United States has established itself as the leading corn producer in the world (Cook, 2006). According to the USDA, the United States produced over 12 billion bushels of corn in 2008 (USDA, 2010). Throughout the past decade, ethanol producers have used an increasing portion of that corn yield, forcing out consumers who demand corn for food and feed, as shown in Figure 4.

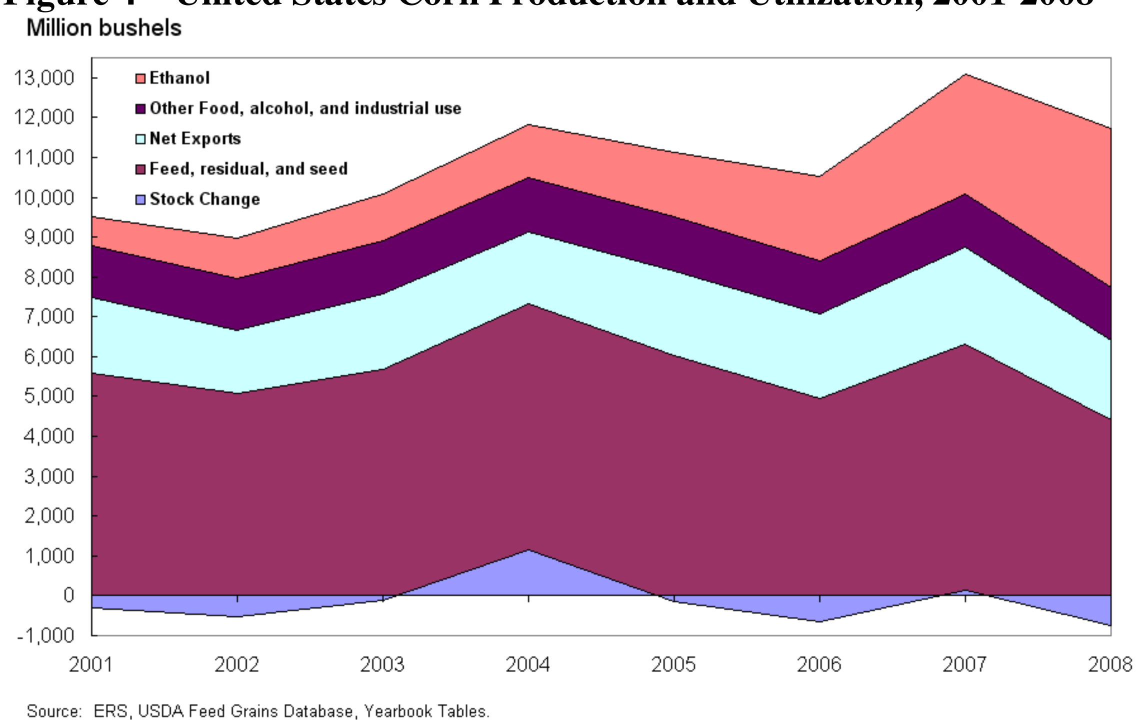
Theoretically, increasing the demand for corn will have a positive impact on the price and quantity produced. Both corn prices and supply have increased over the past decade, which is consistent with economic theory. Corn production has been increasing from 2000 to 2008, but the demand for ethanol has consumed the extra yields and then some. Therefore, corn demanded for food and feed has been crowded out by the increasing prices and the new corn consumers (Baier et al., 2009). In theory, the crowded out, ex-corn consumers would shift to a substitute

Figure 3 – U.S. Corn Production and Use for Ethanol, 1986-2007



Source: USDA National Agricultural Statistics Service and Economic Research Service.

Figure 4 – United States Corn Production and Utilization, 2001-2008



Source: Published by Baier et al. 2009

good. Specifically, demand transfers to wheat and soybeans as substitutes to corn because of their caloric and rotational relationships. Similarly to corn, with increasing demand for food and feed the price and supply of wheat and soybeans should increase.

Theory states that the supply side of the markets for corn, wheat, and soybeans should be affected as well. The rising prices from the growing demand of each commodity will cause a movement along the supply curves, which should be accompanied by a shift in each supply curve. Corn growers cannot just decide to increase their yield per acre. In fact, there are many random factors that could change crop yields such as disease and weather (Wrather and Koenning, 2006). The most effective way for corn farmers to produce larger annual yields is to plant more acres. Since arable land is a rival good, if corn producers use more land, soybeans and wheat should have less land to farm. Theoretically, in this scenario all three market supply curves should shift corn's to the right, and wheat and soybeans' to the left.

Evidence supports the occurrence of the theoretical shifts in the supply curves in the United States. Roughly 300 million acres of land are used for agricultural purposes in the United States. Of those 300 million acres, 220 million are dedicated to growing corn, wheat, or soybeans. This shows that if farmers need more land for corn, they will most likely take land from wheat or soybeans. Soybeans are the most susceptible to a loss in planted acreage because they are commonly planted in a crop rotation with corn on the same land. There is, however, a downside to stopping a crop rotation and only growing corn. Scientists have proven that crop rotation will produce greater yields of each crop because complimentary crops will leach nutrients into the soil that others deplete (Cook, 2006). Even with the threat of lower yields, farmers are beginning to practice more monoculture so they can reap the higher profits of selling corn for fuel instead of wheat or soybeans for food.

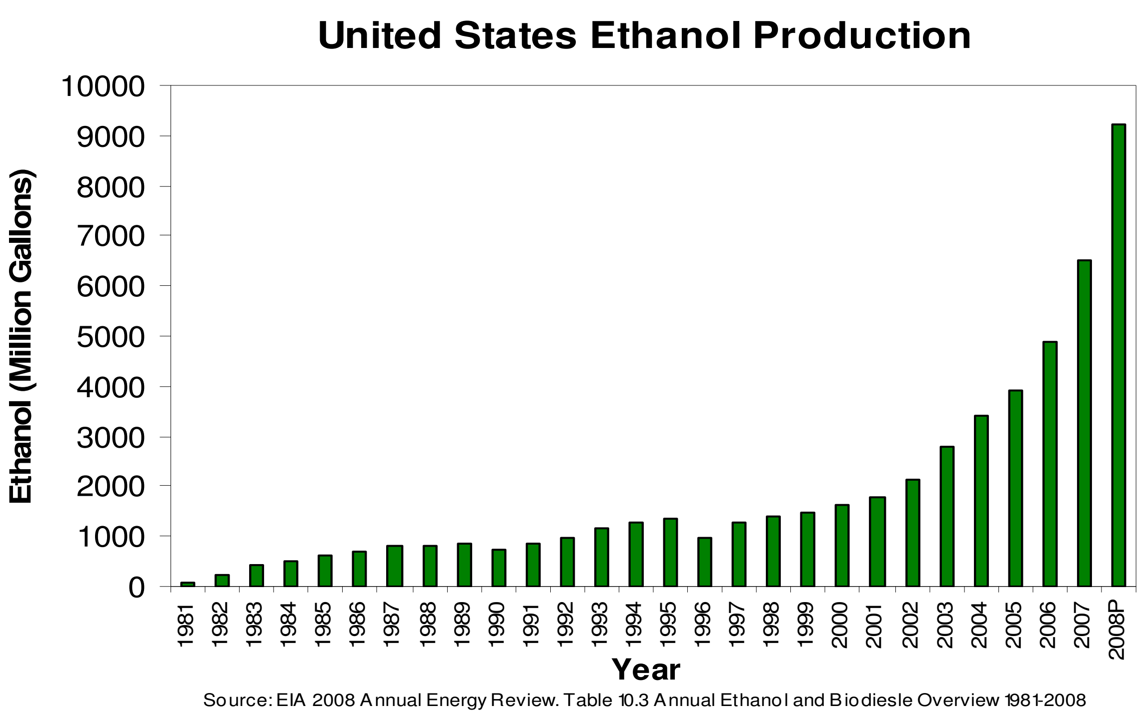
An alternative to increasing planted acreage without pilfering land from wheat or soybeans is simply to farm unused land. Presently, with such high agricultural demands, the most productive arable land is already in use. Less desirable land is sometimes available, but it is often part of the Conservation Reserve Program (CRP). The CRP pays farmers an annual fee for every acre of land defined as "vulnerable" that they do not plant on. Farmers often accept these payments because planting on vulnerable land will increase their workload and diminish their yield per acre due to the lower nutrient contents of the soil. Nevertheless, as the price of corn has gone up, the extra profits farmers could make from planting corn on CRP land have started to compete with CRP payments (Secchi et al., 2009). These trends support the theoretical analysis that crop supply will adjust to the increased ethanol demand.

The United States ethanol policies are attempts at correcting poor national energy security and environmental quality. To some extent, all of the policies have achieved their direct goals through the increasing supply and consumption of ethanol in the U.S.; however, policy makers have overlooked the indirect effects. The policy bundle in place has transferred the deadweight loss present in the ethanol market to the United States' agricultural markets such as corn, wheat, and soybeans. The goal of this paper is to use data collected from the past decade in an empirical study to show ethanol policies have a statistically significant impact on crop prices.

3. Previous Work

Ethanol in the United States is a rapidly expanding market that has caught the interest of economists. The explosion of ethanol into the fuel industry over the last decade left many researches questioning why now? The commodity has been around for over a century, but only recently has it been in high demand, see Figure 5. Many theoretical explanations exist, and the field quickly attempted to prove or disprove them. Ethanol has established itself as an area of study with the potential for copious amounts of research. The multiple policies in place ranging from tariffs to subsidies, dozens of substitution effects across crops and food products, and the presence of positive externalities give many options to those interested in the study of ethanol. This literature review focuses on a subgroup of ethanol papers that investigate ethanol policies and ethanol's impact on crop prices.

Figure 5 - United States Ethanol Production, 1981-2008



A common trend in ethanol literature is the use of long-run stochastic models to predict how crop prices will transform with changes in ethanol demand and production over time.

Elobeid et al. (2007) estimate the long-run supply curve for ethanol by modeling ethanol's profitability. After developing a hypothetical supply curve, the authors use commodity models developed by the Food and Agricultural Policy Research Institute (FAPRI) to predict equilibrium, long-run corn prices. Unfortunately, according to Kruse et al. (2007), the FAPRI models that Elobeid et al. use underestimate the expansion of ethanol market. Kruse et al. explain how the old models will misrepresent the estimates of actual impacts on crop prices. Therefore, the authors correct for Elobeid et al.'s shortcomings by using updated FAPRI models and redefining the demand for ethanol.

It is not surprising that both papers predicted similar outcomes, even with their discrepancies. Elobeid et al. (2007) compared their long-run estimations to 2006 FAPRI baseline estimations and found an increase in corn and wheat prices, while predicted soybeans' price should fall. Kruse et al. (2007) approached their results from the perspective of a policy analysis. Instead of comparing their long-run outcomes to a current baseline, they compared their estimates to potential prices without ethanol tax provisions. Their results led to the conclusion that corn, wheat, and soybean prices will be inflated because of the VEETC.

Along with long-run predictive models, ethanol literature attempts to explain the short-run impacts of ethanol policies on crop prices. McPhail and Babcock (2008) use a set of stochastic and non-stochastic supply and demand models to determine the impact of the RFS, VEETC, and the ethanol tariff on 2009 corn and fuel prices. The authors create their models for crops and fuels from estimated distributions based on historical trends. The models for crops uses 50 years of harvested acreage and yield data collected from the USDA, while their ethanol models are created from ethanol production capacity data collected from the RFA. This is an example of another paper that uses simulation models instead of linear estimation; however, the authors examine a broad policy set in the short-run. The authors only look at the effects on the price of corn, but given the substitutability of corn with wheat and soybeans, McPhail and Babcock's results imply that ethanol policies should have an influence on the price of wheat and soybeans too.

Baier et al. (2009) look at the short-run as well, yet they do not use stochastic models. The authors break down ethanol's effects on crop prices into direct, indirect, and total effects. In calculating direct effects, Baier et al. make an assumption that the change in the demand for a commodity is equal to the change in supply for the commodity. Setting change in demand equal to change in supply, the authors solved for percent change in commodity price as a function of change in ethanol demand. In the end, their results are completely dependant on the chosen elasticities for crops and ethanol. Baier et al. used median elasticity estimates derived from FAPRI data for their study. However, by providing an interactive spreadsheet, the reader had the ability to see the differences in their results using a mean, median, minimum, or maximum elasticity for sensitivity analysis. After selecting the elasticity, the authors combined the calculated direct effects with the indirect, cross-price effects, and found expanding ethanol production was responsible for increases in corn, wheat, and soybean prices. In their conclusion, the authors discuss how their model should be used as a comparative measure for stochastic models because of simulation models' wide range of estimated effects that depend on the chosen assumption. Baier et al. did solve for ethanol's actual influence, but they neglected to investigate the price changes specifically related to ethanol policies.

Another outlook on the ethanol industry's relationship to crop markets focuses on welfare loss associated with ethanol policies. Gardner (2007) and De Gorter and Just (2009) explore the changes in deadweight loss from the addition of the ethanol tax credit to the farm price supports already in place. In both studies, the authors create a simulated supply and demand structure based on historical data collected from the USDA. Using their constructed models, Gardner and De Gorter and Just compare their estimated social welfare under both policies to the social welfare without the VEETC. Through the development of similar framework, the authors both found an increase in deadweight loss from the addition of the ethanol tax credit. Even though neither paper directly solves for the tax credit's impact on corn prices, they do establish a strong theory for such a study to be conducted.

The lack of ethanol papers using non-stochastic or non-simulation models illustrates the youth of the ethanol industry. Kruse et al. (2007) commented that "very little data is available," so most equations used in ethanol studies are "synthetically derived." Even with the majority of the literature involving simulation models, the results are all similar: if ethanol production increases, then corn, wheat, and soybeans' prices increase as well. Papers examining ethanol policies take these results a step further. They show ethanol policies directly affect ethanol production, thus they are a component of increasing crop prices. Since Kruse et al.'s paper was written, a considerable amount of data has become available. Literature on ethanol will soon start to move away from predictive models, towards explanatory models. This paper will attempt to be at the forefront of this transition by exploring historical effects of ethanol policies on crop prices.

4. Data

4.1 Summary of Data[4]

More data is available now than when Kruse et. al published their work, yet there are still many limiting factors on the size of the data set. The first obstacle is the availability of national

[4] See Appendix 2 for a complete list of variables and units

data. Historical yields, prices, and acreage is available for each crop dating back to the late 1800s, but even if all the independent variables were accessible for this long of a time period, the number of observations would still be lacking. To widen the scope of the data set, the variables are taken from the state level instead of the national level. Using state level data is also inhibiting because the independent variables are not recorded in as much detail for states. In order to use all the desired independent variables the range of the data set shrunk a considerable amount. Another restriction on the size of the data set is only 29 out of the 50 states have information available for the variables. In the end, the data set covers the years 2000-2008 for a total of 247 observations, but even with the shortened time period, using state level data increased the overall size of the data set a considerable amount.

The majority of the data was collected from the National Agricultural Statistics Service (NASS), which is a branch of the USDA. The NASS uses annual surveys to accumulate data on all aspects that pertain to United States agriculture. Crop prices, planted acreage, and livestock data were all gathered from the NASS database. The natural logs of corn, wheat, and soybean prices serve as the dependent variables and are calculated using the collected figures. The price variable was calculated using the farm crop price index (FCPI) developed by the USDA to chain crop prices to 2000 dollars. The FCPI was used instead of the national consumer price index (CPI) because the crops used in this study are a specific subgroup of the index. It should provide more accurate adjusted values, thus more accurate end results.

Planted acreage and livestock are two independent variables that should directly affect crop supply and demand. Intuitively, increasing planted acreage should increase crop yields, which would lower prices; however, this is not necessarily the case. Yields are dependant on weather, the quality of the soil, and if the farmer wants to harvest the land (Schlenker and

Roberts, 2009). Even with uncertain increases in yield, cost of production will rise. The farmers will need to use more time, labor, and inputs for every extra acre of land; therefore, with ambiguous changes in yields, prices should rise as cost of production increases.

Livestock is broken down into three types of animals: cattle, hogs, and chickens. These three animals are the main consumers of feed in the United States. Since corn, wheat, and soybean meal are components of animal feed, prices should be affected by the number of animals in each state. The animals are separated by species because there are variances in how much each type of animal can eat in a given year. The production of corn-based ethanol does produce DDGS, which can be used as a feed-grain substitute. However, the quality of the DDGS varies by ethanol plant and their fermentation processes, and many plants refuse to deliver the product to farmers (University of Minnesota, 2010). The unreliability of quality and the transaction costs associated with DDGS imply that livestock farmers will still heavily rely on traditional crops to feed their animals.

Along with the data collected from NASS, other independent variables have been accumulated to depict the characteristics of crops and the ethanol market. The natural log of the gross domestic product (GDP) per capita is an independent variable collected from the Bureau of Economic Analysis (BEA), and is defined using chained 2000 dollars. GDP per capita illustrates two key elements for the demand of each crop: first, it demonstrates each state's purchasing power, and second, it represents the states population.

For an independent variable to embody ethanol supply and demand, the easiest solution would be to add the total gallons of ethanol, yet there are several issues with this. First, the data at the state level is only available in terms of plant capacity, and it does not indicate how efficiently each plant runs. Total possible production can be calculated, but not actual output at the state level. Second, there would be serious multicollinearity between ethanol production and the ethanol policies. Instead, ethanol demand is modeled using a proxy variable that measures the number of flex fuel pumps in each state. A reasonable assumption to make is the more flex fuel pumps, the more ethanol is sold in each state, thus more ethanol demand. For ethanol supply, the natural logs of gasoline prices, measured using chained 2000 dollars, are used. Ethanol profits rely heavily on the price of gasoline, so if gas prices increase ethanol producers would be inclined to increase output (Eidman, 2007). Both of these variables were found in Energy Information Administration (EIA) reports.

The policies are defined using dummy variables. They are equal to one the first year the policy is implemented and every year after, while they are equal to zero otherwise. Since MTBE bans are set at the state level, there is a great amount of variation in the dummy variable, see Table 1. The variations between states with and without bans, as well as the variations in the years the states enacted the bans will be optimal to explore the effects of MTBE bans on crop prices. An interaction term is also included describing the relationship between MTBE, VEETC, and RFS is included.

At this point in the study, the tariff policy will be dropped. The ethanol tariff was established in 1980, so there is no variation in the policy variable across the data set's time frame. From the years 2000-2008 the dummy for tariff is equal to one; therefore, no change in crop prices over the recent decade can be attributed to the tariff. The VEETC and RFS policies, however, were established in the middle of the data set's time range. For the purpose of this study the VEETC and RFS policy variables have been combined into one stacked policy variable. The combined policy variable is a dummy variable equal to one for all states in the years greater than or equal to 2006, and zero otherwise.

Table 1 – State MTBE Bans

State	MTBE Ban	Year
Alabama	No	--
Delaware	No	--
Florida	No	--
Georgia	No	--
Illinois	Yes	2004
Indiana	Yes	2004
Iowa	Yes	2000
Kansas	Yes	2004
Kentucky	Yes	2006
Louisiana	No	--
Maryland	No	--
Michigan	Yes	2003
Minnesota	Yes	2000
Mississippi	No	--
Missouri	Yes	2005
Nebraska	Yes	2000
New Jersey	No	--
New York	Yes	2004
North Carolina	Yes	2008
Ohio	Yes	2005
Oklahoma	No	--
Pennsylvania	No	--
South Carolina	No	--
South Dakota	Yes	2001
Tennessee	No	--
Texas	No	--
Virginia	No	--
West Virginia	No	--
Wisconsin	Yes	2004

Source: EPA

The initial reason behind stacking the policy variables was the description of the VEETC law. A tax credit seems to imply that a blender would be reimbursed when filing taxes in April. The assumption is that for filings done in April, the benefits of the VEETC would not be realized until around June. Therefore, blenders would not realize the full benefits of the policy until June 2006, after they had built up a years worth of ethanol credits. This assumption proved to be false. Under the United States' Internal Revenue code 6247, a claim for blending ethanol can be filed for any period longer than one week if the value of the claim is greater than $200. The Secretary has up to 45 days to pay the blender without being charged interest (Cornell University Law School, 2010). Following the rules of the tax code, blenders could receive benefits of the VEETC as early as the end of mid-February, 2005.

It is still essential to stack the policies, even without the support of the tax code. The justification is the lack of a time gap between the implementation of the VEETC and RFS. There is not a sufficient amount of time to measure the effects of the VEETC on crop prices separate from the influence of the RFS. Also if the policies were separated, an interaction should be included to see if the combine effects outweigh the individual effects of each policy. In this case, the interaction term would be equivalent to the RFS dummy variable and would cause perfect multicollinearity. Therefore, the decision was made to solely use a stacked policy variable, synonymous to the interaction term between VEETC and RFS.

4.2 Theoretical Relationships

At first glance the data seems to support the theory of increasing crop prices after the implementation of ethanol policies. Table 2 depicts the percent changes in prices and yields for each crop, and population over the nine years. The values are defined as the percent changes for the United States and the average percent changes for the states used in the regression. Even though only 29 states are included in the study, the similarities between U.S. changes and state average changes suggest that the sample should be a good estimate of the population.

Looking at the years 2005 and 2006 when the VEETC and RFS policies began being enforced, one can see large positive price changes in corn and wheat, as well as modest price increases for soybeans. The increasing price trend continues into the next year, and it is not until 2008 that prices begin to level off. Corn appears to be the most influenced by the shocks in 2005-

Table 2 – Percent Changes

Year	Region	Percent Change in Price			Percent Change in Yield			Percent Change in Population
		Corn	Wheat	Soybeans	Corn	Wheat	Soybeans	
2000-2001								
	United States	3.26	2.89	-6.45	-4.16	-12.60	4.82	1.03
	State Averages	3.94	7.43	-6.54	-3.91	-9.90	4.22	0.69
2001-2002								
	United States	11.04	20.74	19.04	-5.64	-17.54	-4.65	0.95
	State Averages	13.79	15.98	20.29	-5.81	-19.81	-5.71	0.70
2002-2003								
	United States	-1.33	-9.66	25.56	12.50	45.99	-10.97	0.88
	State Averages	-5.77	-2.46	24.73	12.44	58.25	-12.39	0.67
2003-2004								
	United States	-17.84	-3.48	-24.52	17.03	-8.00	27.30	0.94
	State Averages	-15.40	-1.15	-24.70	17.45	-14.24	29.49	0.76
2004-2005								
	United States	0.59	4.21	2.16	-5.87	-2.48	-1.78	0.92
	State Averages	-0.01	4.29	2.49	-6.15	-3.21	-2.00	0.75
2005-2006								
	United States	40.60	15.22	5.08	-5.23	-14.02	4.18	0.96
	State Averages	35.24	5.50	4.55	-5.28	-13.84	3.74	0.66
2006-2007								
	United States	16.75	28.55	32.74	23.80	13.42	-16.25	1.00
	State Averages	16.23	28.98	36.68	22.29	13.91	-16.86	0.95
2007-2008								
	United States	-21.51	-11.30	-22.59	-7.26	21.85	10.83	0.93
	State Averages	-15.46	-7.24	-25.09	-7.27	33.06	11.00	0.80

Source: Price and Yield Data – NASS-USDA
Population Data – US Census Bureau

2006, shown by a 35.2 percent jump in average state prices. In regards to price stability, soybeans are the most volatile. Over the time period, the state average price for soybeans rises or falls by at least 20 percent on five occasions.

The changes for corn prices are illustrated in Figure 6a.[5] The graph confirms that there is a substantial increase in corn prices in the year 2006. At first it seems that the price increase is due to falling yields, shown in Figure 6b. With lower yields farmers would charge more according to the laws of supply and demand. However, in 2007 there is a large increase in yields and a significant increase in crop prices. Decreasing supply is no longer a factor and these movements are consistent with the theory of a demand shift in the corn market.

Wheat prices demonstrate the most stability over the time period. As shown in Figure 7a, from 2000-2005 there is a very smooth upward trend in prices, with a slight jump in 2002. The jump is most likely due to the production of the lowest wheat yields over the nine year period, see Figure 7b. Once the ethanol policies were implemented the smooth, linear growth seems to become exponential over the next two years. The rising wheat prices in 2006 and 2007 are paired with increasing yields, similar to the trends for corn prices. These movements indicate a shift in demand, which could be associated with the substitution effect discussed in the theory section.

The state averages for soybean prices are particularly analogous to the United States' soybean price, as shown in Figure 8a. The similarity is consequence of the particular states included in the data set. A limiting factor for the cross-sectional state data is that soybeans are grown in far less states than wheat and corn. The sum of state yields for soybeans represent a much larger portion of U.S. totals than corn or wheat does. Soybeans' prices do not move a considerable amount in 2005 or 2006, but 2007 there is a large positive increase. However,

[5] See Appendix 3 for Figures 6-8

unlike with corn and wheat, the price increase is paired with a yield decrease, as shown in Figure 8b. Overall, soybeans have the most apparent relationship between quantity supplied and price. This reflects negatively on the theory because the influence of a yield decrease could have a greater impact on soybean prices than the substitution effect from ethanol policies. Thus, the price changes seen in Table 2 might not have any relationship with the VEETC or RFS.

Generally the percent change in prices fit the theoretical model, yet the percent changes in crop yields by themselves do not seem to follow the trend of the theory. As shown in Table 2, all three crops experience extreme volatility in their yields from 2000-2008. Theory indicates that yields should increase after the ethanol polices are put in place, yet corn and wheat yields fall from 2005-2006 and soybean yields do the same from 2006-2007. The instability of the crops' yields can be explained through the randomness associated with growing plants. Wolfram Schlenker and Michael J. Roberts (2009) discuss how different global warming scenarios will change crop yields. The authors explain that corn and soybeans have a critical temperature of 29^{o} C and 30^{o} C, respectively, where there is a modest increase in yield as temperatures rise and a sharp decrease after the critical temperature is reached. Disease is also a factor of instability. J. Allen Wrather and Steve R. Koenning (2006) describe the destruction of soybean yields associated with over 23 diseases. The randomness of weather and disease on crop yields are explanations as to why there are no consistent trends over the time period.

Price trends give the impression that something significant happened in the years 2005 and 2006. It could be a case of correlation not causation, but the available data justifies investigation into the cause. Theory presents a strong case that ethanol policies are the cause of such shifts.

5. Methodology

The combination of all available data resulted in a panel data set. The cross-sectional elements are the 29 states and the time series elements are the years from 2000-2008. There are a total of 247 observations spread over the nine year time period. The panel data set is unbalanced because Delaware and Kansas only have observations available for the years 2000 and 2001. Overall the data set is not large, but it is sufficient to test the hypotheses of ethanol policies effects on crop prices.

Cross-sectional, time series data sets are used to increase the number of observations, but many issues arise as well. First, there is a loss in degrees of freedom. Not only will there be dummy variables for each year, but possible dummies for every state. This could be a problem because of the relatively small number of observations. Second, time series data sets are usually absent of heteroskedasticity and cross-sectional data sets usually do not have serial correlation, but both are possible in panel data sets. Using states as a grouping variable will possibly result in heteroskedasticiy because of the large variations in size and population. Also serial correlation is a possibility due to the time series, and it must be tested for (Darnell, 1994).

Another possible issue with the time series aspect of the data set is a spurious correlation. If the dependant variable and an independent variable move together based on a trend over time instead of a causal relationship, then the fit and t-scores will be overstated (Studenmund, 2006). Adjusting all dollar values to the year 2000 dollars was an attempt to avoid spurious correlation. Eliminating inflation will remove a common trend between all variables that are measured in dollar units, yet the resulting data set could still be non-stationary. Another approach to solve for spurious correlation is to include year dummy variables to absorb the year-to-year trends and avoid inflated fit and t-scores.

Once year dummies are added, the data set is complete and the model can be built. A common modeling technique for examining policy intervention is difference-in-difference estimations; however, this approach will not work for this study. For difference-in-difference estimations there must be a control group that is not affected by the policy. The stacked policy variable is a federal policy defined as a dummy variable that is equal to one for all states starting January 1st, 2006. There would be no states that are unaffected, thus there is no control group. Another technique found in ethanol literature is to use simultaneous equations when developing predictive models, yet simultaneous equations will also be suboptimal in this case. It is uncommon to run simultaneous equations using panel data, since simultaneous equations are run using time series, not cross-sectional, data sets. This claim is supported by the fact the STATA regression software does not have a command to run simultaneous regressions with a panel data. Also, to avoid bias, simultaneous equations need a large sample size of time periods, which is not present in this data set. These problems are avoided by using a hedonic model as an alternative to simultaneous equations or a difference-in-difference approach.

Hedonic regressions model the dependant variable as a function of independent variables that represent the quality of the product. Explanatory variables that define market conditions are omitted from hedonic regressions because such variables often imply simultaneity. As a result, all explanatory variables are assumed to be exogenous. An assumption that must be made is that the qualities of a crop are varying between states and years. This is a reaching assumption, but not an improbable one. Transaction costs from state to state could create a bias towards home grown production. The resulting hedonic equation is modeled as

$$\ln PRICE(X)_{it} = \beta_0 + \beta_1 STACKED_{it} + \beta_2 MTBE_{it} + \beta_3 INTERACT_{it} + \beta_4 PLANT\ ACRE(X)_{it} + \beta_5 FLEX_{it} + \beta_6 CATTLE_{it} + \beta_7 HOGS_{it} + \beta_8 CHICKENS_{it} + \beta_9 \ln GDP/CAP_{it} + \beta_{10} \ln GAS_{it} + \beta[YEAR_{it}] + \varepsilon_{it} \quad (1)$$

$$i = \{1,2,\ldots,29\} \qquad t = \{1,2,\ldots,9\}$$

where $\ln PRICE(X)_{it}$ is the independent variable equal to the natural log of the price of commodity X (i.e. corn, wheat, or soybeans) and ε_{it} is an error term. The variables $STACKED_{it}$, $MTBE_{it}$, and $INTERACT_{it}$, represent the stacked policy, MTBE bans, and interaction term, respectively. The $\beta[YEAR_{it}]$ term is included to show that dummy variables for years are included in the equation. The remaining independent variables are defined in the data section and Appendix 2, and they represent the individual quality characteristics of i^{th} state's commodity.

An alternative to combining all policy variables in one equation would be to separate them. The hypothesis would be that there is insignificant correlation between the effects of each policy on the prices' of the commodities. Through the separation of the policy variables and the removal of the interaction term, it would also be possible to test for a dominant policy variable. Testing a single policy variable's effect on crop prices and comparing the results to the combine effect will act as sensitivity analysis. The two separate policy models are

$$\ln PRICE(X)_{it} = \beta_0 + \beta_1 STACKED_{it} + \beta_2 PLANT\ ACRE(X)_{it} + \beta_3 FLEX_{it} + \beta_4 CATTLE_{it} + \beta_5 HOGS_{it} + \beta_6 CHICKENSit + \beta_7 \ln GDP/CAP_{it} + \beta_8 \ln GAS_{it} + \beta[YEAR_{it}] + \varepsilon_{it} \quad (2)$$

$$i = \{1,2,\ldots,29\} \qquad t = \{1,2,\ldots,9\}$$

$$\ln PRICE(X)_{it} = \beta_0 + \beta_1 MTBE_{it} + \beta_2 PLANT\ ACRE(X)_{it} + \beta_3 FLEX_{it} + \beta_4 CATTLE_{it} + \beta_5 HOGS_{it} + \beta_6 CHICKENSit + \beta_7 \ln GDP/CAP_{it} + \beta_8 \ln GAS_{it} + \beta[YEAR_{it}] + \varepsilon_{it} \quad (3)$$

$$i = \{1,2,\ldots,29\} \qquad t = \{1,2,\ldots,9\}$$

After the construction of the initial hedonic models, more specification is needed. Regressions using panel data can be specified using fixed-effects or random-effects. A fixed-effects model will allow states to have different intercepts. It is synonymous to adding dummy variables for the cross-sectional states. Using fixed-effects will remove omitted variable bias for state characteristics that do not change over time. For example, the size of the state or amount of arable land does not need to be included for each state because they are fixed over the time period. Conversely, a random-effects model will allow for a different intercept for each cross-sectional variable, which is taken from a distribution centered around the mean intercept. An advantage of random-effects is greater degrees of freedom resulting from the omission of the fixed-effect, state dummy variables (Studenmund, 2010).

The proper test to determine whether equation (1) should be modeled using fixed- or random-effects is the Hausman specification test. The Hausman test compares the estimated β_s from a fixed-effects model to the estimated β_s of a random-effects model. The null hypothesis is the coefficients of the fixed- and random-effects equations are not significantly different. If the null hypothesis is rejected, then the appropriate regression model is a fixed-effects model. Conversely, if null is not rejected, a random-effects model is used (Studenmund, 2010). Both models can be used if the null is not rejected, but the random-effects model is more efficient due to a smaller variance of the coefficients (Griliches and Intriligator, 1984). The results of the Hausman test on equation (1) are shown in Table 3. The null hypothesis is rejected at a five percent level of significance for wheat, and H_0 is not rejected for corn or soybeans. To ensure the interpretation of estimates is consistent between models, the specification of equations (2) and (3) will be identical with the results of the Hausman test on equation (1). Also for sensitivity analysis, the model for corn and soybean prices will be estimated using both fixed- and random-effects models.

Table 3 – Hausman Test

Commodity	Policy (Equation)	Chi^2	Reject H_0[1]	Random or Fixed
Corn	COMBINE (1)	Chi^2(11) = 19.16	No	Random Effects
Wheat	COMBINE (1)	Chi^2(11) = 28.95	Yes**	Fixed Effects
Soybeans	COMBINE (1)	Chi^2(11) = 10.58	No	Random Effects

[1] H_o: Coefficients from fixed effects and random effects are not statistically different
* 10% Level of Significance
** 5% Level of Significance

After the models are specified according to the Hausman test results, the model must be tested, and corrected, for serial correlation and heteroskedasticity. According to David M. Drukker (2003) the simplest test for serial correlation in fixed- or random-effects models is one developed by Jeffery Wooldridge in 2002. Drukker uses a Monte Carlo derived panel data set with varying degrees of serial correlation. To inspect the power of Wooldridge's test, he specifies models using fixed- or random-effects and compares their outputs. His results imply that with ρ equal to, or greater than, .2, the rejection of the null hypothesis of no serial correlation is close to 100 percent. An alternative method described by Badi H. Baltagi, Byoung Cheol Jung, and Seuck Heun Song (2008), uses a joint lagrange multiplier test to examine serial correlation and heteroskedasticity simultaneously. The mathematics of their test is beyond the capacity of this paper; therefore, the Wooldridge test is will be used on equations (1), (2), and (3) for each commodity. For each equation the null hypothesis is rejected, as shown in Table 4, which suggests serial correlation in all equations.

Table 4 – Wooldridge Test

Commodity	Policy (Equation)	F-Stat	Reject H_0[1]
Corn	COMBINE (1)	F(1, 26) = 26.00	Yes**
	STACKED ONLY (2)	F(1, 26) = 48.93	Yes**
	MTBE ONLY (3)	F(1, 26) = 48.43	Yes**
Wheat	COMBINE (1)	F(1, 26) = 24.81	Yes**
	STACKED ONLY (2)	F(1, 26) = 24.81	Yes**
	MTBE ONLY (3)	F(1, 26) = 24.82	Yes**
Soybeans	COMBINE (1)	F(1, 26) = 6.670	Yes**
	STACKED ONLY (2)	F(1, 26) = 6.392	Yes**
	MTBE ONLY (3)	F(1, 26) = 6.754	Yes**

[1] H_o: No serial Correlation
* 10% Level of Significance
** 5% Level of Significance

With the presence of serial correlation in all models, ordinary least squares (OLS) is no longer the best linear, minimum variance estimator. Using OLS will result in biased standard errors and inconsistent hypothesis testing; therefore, an AR(1) method is chosen to account for the serial correlation. Marianne Bertrand, Esther Duflo, and Sendhil Mullainathan (2004) discuss the most effective correction method for autocorrelation using panel data in difference-in-difference models. The authors found the AR(1) method increases the accuracy of the standard errors of the estimated coefficients as the number of groups and length of the time period decrease. Due to the small number of state groups and short time frame, AR(1) should produce reliable standard errors. Assuming their findings are true across all panel data sets and not specific to difference-in-difference estimations, AR(1) is the proper technique to use.

There is still a possibility of heteroskedasticity that could cause bias in the standard errors of the coefficients, even after serial correlation is corrected for. For this study, the possibility of heteroskedasticity will be ignored. A common approach to correcting for heteroskedasticity in panel data is to use cluster errors that take into account changing variances in the grouping variable, i.e., states. According to Kurt Schmidheiny's lecture (2009) on clustering, this technique should only be performed on larger data sets where there are more than 50 groups. The small size of the data set inhibits further specification. Baltagi et al. (2008) imply that the process of correcting for serial correlation and ignoring heteroskedasticity, or vice versa, is a common in economics literature using panel data. The test the authors develop would be appropriate, but once again the complexity of Baltagi et al.'s lagrange multiplier test prevents its use in this study. Therefore, this paper will follow an existing trend and only adjust standard errors for one of the possible biases.

In the next section, the model that has been developed will be used to test the influence of ethanol policies on corn, wheat, and soybean prices. The first attempt at finding an impact will be through the use of the Chow test. The Chow test was developed by Gregory C. Chow, and is used to test if a policy has a statistically significant impact on a dependant variable. The test requires a break in the time series, where the policy is not present before a given year and is present after. The test involves running a regression on the dependant variable before the policy, after the policy, and across the combine time period, then comparing the sum of squared residuals from each regression (Chow, 1960)[6]. After the Chow test is run, the actual coefficients will be estimated using an AR(1) method specified for panel data.

6. Results

The Chow test will only be appropriate for equations including the $STACKED_{it}$ variable because it has a defined break year; therefore, only equations (1) and (2) will be tested. The test results conclude if the slopes of the coefficients are statistically different before and after the break year. If the null hypothesis—the slope estimates are the same—is rejected, then the

[6] See Table 5 for the equation

influence of the policies carries statistical significance. The Chow test is useful in testing whether or not there is a meaningful effect, but there is no conclusion as to what the magnitude of the effect is. Using the AR(1) method to run the regressions on derived equations will show what the actual size of the impact is.

Table 5 shows the results of the Chow test on each commodity for equation (1) and (2). According to the initial test, wheat should be the only commodity that rejects the null hypothesis; therefore, it is the only commodity affected by the implementation of the VEETC and the RFS. Intuitively, this conclusion does not make sense. If ethanol policies are responsible for the price increase in wheat, then the effect would have to be an indirect from wheat's relationship with corn. Logically if corn is unaffected as shown in the Chow test, then both wheat and soybeans should be unaffected as well. Also looking back at Figure 7a, wheat's yield is clearly increasing after the break year, so the Chow test is not contributing the effects of a decrease in wheat yield to the policy variables. This would normally cause one to be hesitant when interpreting the regression for wheat, except other discrepancies are apparent in Table 5.

Another disturbing result from the Chow test is the negative F-stats for soybeans' equations. A negative result indicates that the summation of the before and after regressions' sum of squared residuals are greater than the combine regression's sum of squared residuals. This implies that the estimates of the regression models before and after the break year had a substantially worse fit than the combine model. Further research shows no signs of any other authors recording negative results for Chow tests. Two possibilities arise for the cause behind the negative F-stats. First, the AR(1) method is not compatible with the Chow test because of how the residuals are calculated. Second, the Chow test is not appropriate when an equation is specified as a random-effects model. Again the mathematics behind the Chow test and the AR(1)

Table 5 – Chow Test

Commodity	Policy (Equation)	Variables	Chow Test F-Stat	Reject Null
Definitions	COMBINE (1) Break Year = 2006 STACKED (2) Break Year = 2006	S_c^2 = sum of squared residuals for the combined equation p = parameters S_1^2 = sum of squared residuals pre-break year S_2^2 = sum of squared residuals post-break year df = degrees of freedom	$\text{F-stat}=\dfrac{\dfrac{S_c^2-(S_1^2+S_2^2)}{p}}{\dfrac{(S_1^2+S_2^2)}{(df_1+df_2)}}$	H_0: β_1s = β_2s H_1: β_1s ≠ β_2s
Corn	COMBINE (1)	S_c^2 = 0.8154 p = 17 S_1^2 = 0.3477 df_1 = 152 S_2^2 = 0.4371 df_2 = 70	F(17, 222) = .5092	No
	STACKED (2)	S_c^2 = 0.7989 p = 16 S_1^2 = 0.3347 df_1 = 153 S_2^2 = 0.4382 df_2 = 71	F(16, 224) = .4707	No
Wheat	COMBINE (1)	S_c^2 = 0.8678 p = 44 S_1^2 = 0.3799 df_1 = 96 S_2^2 = 0.1239 df_2 = 18	F(44, 114) = 1.830	Yes**
	STACKED (2)	S_c^2 = 0.8740 p = 43 S_1^2 = 0.3917 df_1 = 97 S_2^2 = 0.1183 df_2 = 19	F(43, 116) = 1.882	Yes**
Soybeans	COMBINE (1)	S_c^2 = 0.4028 p = 17 S_1^2 = 0.1518 df_1 = 152 S_2^2 = 0.3313 df_2 = 70	F(17, 222) = -2.171	No
	STACKED (2)	S_c^2 = 0.4116 p = 16 S_1^2 = 0.1536 df_1 = 153 S_2^2 = 0.2619 df_2 = 71	F(16, 224) = -0.1314	No

* 10% Level of Significance
** 5% Level of Significance

method are too advanced for this paper to search their proofs for compatibility. Assuming that the results for wheat are accurate, this would rule out AR(1) as the source of the problem. Seeing as how both corn and soybeans use random-effects, and there are issues with both commodities F-stats, the assumption is that the sum of squared residuals in random-effects do not agree with the Chow test.

The Hausman test revealed that random-effects should be used when running regressions on the prices for corn and soybeans; however, fixed-effects can also be used. The results from the Hausman test imply that random-effects will be a more efficient estimator of the coefficients.[7] If fixed-effects are used the standard errors will inflate, but it will not cause bias in the coefficients. Running the Chow test again on equations (1) and (2) for corn and soybean prices under a new specification reveals more promising results, see Table 6. The null hypothesis for all four equations is rejected, showing that the stacked ethanol policies do have an impact on corn and soybean prices.

Before respecifying the models for corn and soybeans, the regressions were run using the specifications derived from the Hausman test. The estimates of the coefficients and the standard errors are recorded in Table 7. Inspecting wheat first since the initial Chow test proved effective, shows that the policy stack in equations (1) and (2) has a considerable influence on the price of wheat. The STACKED policy is responsible for a 9.4 percent increase in the price of wheat in equation (1) and a 10.9 percent increase in the price in equation (2). However, MTBE and INTERACT are not statistically significant. Equation (3) tests to see if STACKED is a dominant variable, but the outputs confirm that MTBE has no statistical significance. Even as the lone policy variable, the implementation of an MTBE ban has no effect on wheat prices. The worse fit

[7] Actually, random-effects could cause bias in the coefficients due to omitted variables that characterize states

Table 6 – Chow Test Sensitivity Analysis

Commodity	Policy (Equation)	Variables	Chow Test F-Stat	Reject Null
Corn	COMBINE (1)	S_c^2 = 0.6394 p = 44 S_1^2 = 0.2244 df_1 = 96 S_2^2 = 0.1459 df_2 = 18	F(17, 222) = 1.883	Yes**
	STACKED (2)	S_c^2 = 0.6397 p = 43 S_1^2 = 0.2256 df_1 = 97 S_2^2 = 0.1446 df_2 = 19	F(16, 224) = 1.964	Yes**
Soybeans	COMBINE (1)	S_c^2 = 0.3450 p = 44 S_1^2 = 0.1184 df_1 = 96 S_2^2 = 0.0962 df_2 = 18	F(17, 222) = 1.575	Yes**
	STACKED (2)	S_c^2 = 0.3494 p = 43 S_1^2 = 0.1187 df_1 = 97 S_2^2 = 0.0957 df_2 = 19	F(16, 224) = 1.699	Yes**

* 10% Level of Significance
** 5% Level of Significance

in equation (2) and (3)[8] compared to equation (1), and the strong theoretical evidence for keeping the MTBE and INTERACT variables, implies that the results of equation (1) are the most accurate.

The output for the effects of STACKED, MTBE, and INTERACT are more convoluted for corn and soybeans than wheat. The conclusions drawn from the first Chow test imply the STACKED policy variable for equation (1) and (2) should not be statistically significant for both corn and soybeans. However, three out of the four equations produced statistically significant coefficients. This supports the assumption that the Chow test is not compatible with random-effects specification.

[8] Equation (3)'s fit does fall slightly, but appears the same as equation (1) due to rounding

Table 7 – Results

Variables	lnPRICE(Commodity) [Effect Specification] (Equation)								
	lnPRICE(CORN) [Random Effects]			lnPRICE(Wheat) [Fixed Effects]			lnPRICE(Soybeans) [Random Effects]		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
STACKED	0.185 (0.134)	0.389** (0.123)	--	0.0940** (0.0470)	0.109** (0.0389)	--	0.162** (0.0811)	0.150** (0.0732)	--
MTBE	-0.0517** (0.0183)	--	-0.0148 (0.0163)	-0.0341 (0.0279)	--	-0.0271 (0.0243)	-0.0233** (0.0113)	--	-0.0159* (0.00957)
INTERACT	0.0819** (0.0236)	--	--	0.0164 (0.0319)	--	--	0.00760 (0.0156)	--	--
PLANT ACRE	-1.07e-5** (3.32e-6)	-1.45e-5** (3.28e-6)	-1.22e-5** (3.30e-6)	-0.000121** (4.03e-5)	-0.000122** (3.96e-5)	-0.000118** (3.97e-5)	2.42e-6 (1.86e-6)	6.09e-7 (1.70e-6)	2.58e-6 (1.85e-6)
FLEX	-0.000208 (0.000179)	8.01e-7 (0.000173)	0.000103 (0.000172)	-0.000119 (0.000287)	-7.88e-5 (0.000267)	-6.55e-5 (0.000266)	0.000125 (0.000103)	0.000113 (9.97e-5)	0.000181* (9.92e-5)
CATTLE	1.55e-6 (2.94e-6)	1.50e-6 (1.65e-6)	1.73e-6 (2.97e-6)	4.86e-5 (7.10e-5)	4.51e-5 (7.03e-5)	5.19e-5 (7.05e-5)	-2.84e-6** (1.30e-6)	-3.12e-6** (1.34e-6)	-2.71e-6** (1.33e-6)
HOGS	7.46e-8 (1.55e-6)	5.63e-7 (1.56e-6)	5.00e-7 (1.58e-6)	-1.84e-6 (3.25e-6)	-1.90e-6 (3.22e-6)	-1.67e-6 (3.22e-6)	-3.81e-9 (8.01e-7)	7.51e-8 (8.20e-7)	-1.31e-7 (8.12e-7)
CHICKENS	8.89e-7* (5.36e-7)	9.52e-7* (5.78e-7)	8.13e-7 (5.45e-7)	-1.35e-6 (1.75e-6)	-1.39e-6 (1.75e-6)	-1.40e-6 (1.74e-6)	2.93e-7 (2.50e-7)	3.00e-7 (2.59e-7)	2.55e-7 (2.57e-7)
lnGDP/CAP	0.0458 (0.0493)	0.0563 (0.0532)	0.0323 (0.0490)	0.237 (0.294)	0.0318 (0.286)	0.248 (0.292)	-0.0163 (0.0234)	-0.0225 (0.0239)	-0.0314 (0.0231)
lnGAS	0.0460 (0.208)	-0.258 (0.195)	0.358 (0.290)	-0.419 (0.311)	-0.508* (0.284)	-0.483* (0.285)	-0.0662 (0.125)	-0.0547 (0.115)	0.186** (0.0192)
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	.875	.870	.859	.768	.765	.768	.933	.932	.932

* 10% Level of Significance
** 5% Level of Significance

For corn, equation (1) does not produce a statistically significant coefficient for STACKED. Also, converse to wheat, MTBE and INTERACT both have significant coefficients. Oddly, the coefficient for MTBE is negative when theory indicates it should be positive. A possible explanation is that all ten of the top corn yielding states banned MTBE. Naturally with a greater supply of corn, prices will be lower than other states. This leads one to believe that the estimated negative effects of MTBE on corn prices are most likely a case of correlation not causation.

The INTERACT variable for corn is also hard to interpret. It does not seem reasonable that INTERACT has statistical significance in the positive direction, while STACKED is insignificant and MTBE is significant in the negative direction. Contrary to equation (1), the STACKED coefficient in equation (2) is statistically significant and has more than doubled. Theoretically it does not make sense that the VEETC and RFS should only affect corn prices when MTBE bans are in place. It is possible that INTERACT is significant and STACKED experiences omitted variable bias in equation (2). However, theory does not support this conclusion. An explanation is the INTERACT variable is acting as a dominant variable in equation (1) and is absorbing most of STACKED's effect. Therefore, none of the coefficients for the policy variables in equation (1) for corn can be inferred to be actual effects.

The regression results for soybeans do not indicate the presence of a dominant variable. The results show the estimate for the coefficient of the STACKED policy is statistically significant in both equations (1) and (2). According to equation (1), passing both federal ethanol policy measures inflated the price of soybeans by 16.2 percent. The larger effect on soybeans compared to the effect on wheat is consistent with the theory. Soybeans are more substitutable with corn in animal feed, as well as in planted acreage; therefore, the indirect effect should be greater on soybeans. Similar to corn, there is a statistically significant negative relationship between MTBE bans and the price of soybeans. Again it is most likely a case of correlation not causation, as nine out of the top ten soybean yielding states have banned MTBE.

The validity of the results using random-effects for corn and soybeans is questionable. As discussed above, it is acceptable to use a fixed-effects specification when the null hypothesis of the Hausman test is not rejected. It is not recommended because fixed-effects are less efficient and there is large loss in degrees of freedom from the addition of state dummy variables; however, there is possible omitted variable bias when using random-effects models. The results from the second Chow test imply that STACKED has a statistically significant effect on the price of corn and soybeans when a fixed-effects specification is used instead of random effects. For sensitivity analysis, equation (1), (2), and (3) will be run again for corn and soybeans with a fixed-effects specification.

The results of the regressions for corn and soybeans using fixed-effects are recorded in Table 8. The first numbers that jump out are the large, statistically significant coefficients of STACKED for corn's equations (1) and (2). Focusing on equation (1) as the superior of the three, the establishment of the VEETC and RFS are responsible for a 30 percent increase in corn prices. An interesting observation is that the coefficients for MTBE and INTERACT did not change by more than a standard deviation after the transformation. MTBE's coefficient did lose statistical significance, while INTERACT's continues to have significance. Corn prices are shown to increase by 8.22 percent due to the interaction between MTBE bans and the implementation of the VEETC and RFS. It is also the only commodity that is significantly affected by the interaction. The implication is that the corn market is originally affected by the

Table 8 – Adjusted Specification Results

Variables	lnPRICE(Commodity) [Effect Specification] (Equation)					
	lnPRICE(CORN) [Fixed Effects]			lnPRICE(Soybeans) [Fixed Effects]		
	(1)	(2)	(3)	(1)	(2)	(3)
STACKED	0.300** (0.0390)	0.368** (0.0329)	--	0.0643** (0.0284)	0.0573** (0.0238)	--
MTBE	-0.0341 (0.0229)	--	0.00307 (0.0201)	-0.0153 (0.0165)	--	-0.0191 (0.0139)
INTERACT	0.0822** (0.0261)	--	--	-0.00818 (0.0191)	--	--
PLANT ACRE	3.43e-5 (2.23e-5)	3.67e-5 (2.28e-5)	3.60e-5 (2.29e-5)	2.86e-5* (1.68e-5)	3.20e-5* (1.67e-5)	2.92e-5* (1.68e-5)
FLEX	-0.000433* (0.000245)	-0.000157 (0.000232)	-0.000160 (0.000235)	0.000231 (0.000178)	0.000205 (0.000166)	0.000207 (0.000166)
CATTLE	-6.56e-5 (5.90e-5)	-4.36e-5 (5.96e-5)	-4.55e-5 (6.02e-5)	-1.48e-5 (4.35e-5)	-2.10e-5 (4.32e-5)	-1.70e-5 (4.32e-5)
HOGS	-1.27e-06 (2.72e-06)	-3.95e-07 (2.77e-06)	-4.17e-07 (2.78e-06)	2.92e-06 (2.07e-06)	2.69e-06 (2.06e-06)	2.81e-06 (2.05e-06)
CHICKENS	1.58e-06 (1.40e-06)	1.33e-06 (1.41e-06)	1.36e-06 (1.43e-06)	-5.84e-07 (9.69e-07)	3.00e-7 (2.59e-7)	-5.52e-07 (9.76e-07)
lnGDP/CAP	-0.374 (0.242)	-0.327 (0.238)	-0.320 (0.248)	-0.0121 (0.170)	0.0439 (0.165)	-0.0149 (0.170)
lnGAS	-0.192 (0.254)	-0.508** (0.236)	-0.512** (0.239)	-0.182 (0.183)	-0.162 (0.168)	-0.150 (0.168)
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	.869	.863	.861	.933	.932	.932

* 10% Level of Significance
** 5% Level of Significance

policies' interactions, but the impact on corn is not strong enough to carry over into the substitute markets.

Another change for corn between Table 7 and Table 8 is the increase in magnitude and statistical significance for the coefficients of PLANT ACRE. The addition of state dummies under fixed-effects is most likely responsible for this change. Through the use of a random-effects specification the coefficients for PLANT ACRE took on negative signs, contradicting theory. Most likely without state dummies, planted acreage acts as a proxy variable for yield and size of the state. Both of these effects would be absorbed when state dummy variables are included, and explain why the signs changes from Table 7 to Table 8.

The final regressions use a fixed-effects model for soybean prices, and the estimated coefficients are listed in Table 8. The change from a random-effects model to a fixed-effects model had a drastic impact on the size of the coefficients for STACKED. The values are still statistically significant, but they are less than a half of the previous value for equation (1) and a third the value for equation (2). Equation (1) depicts a 6.43 percent increase in soybean prices with the stacked policies in place, while equation (2) shows a 5.73 increase. These values are the smallest for any of the three commodities. Seeing as how soybeans experience the greatest volatility in yields over the time period, these results are rational. With varying yields it would be difficult to distinguish between the impact of STACKED and the impact of yields. The resulting outcome is a lower than expected coefficient for STACKED and an inflated coefficient for the 2007 year dummy that carries strong statistical significance. The year dummy acts as a proxy for random occurrences, and an exceptionally poor yield could be the consequence of those factors.

A concern with the results is why MTBE does not have a positive impact on corn prices. Theoretically, corn prices should rise as the demand for ethanol increases to substitute for less use of MTB. Indirectly wheat and soybean prices should rise as well. The variation in states and years that banned MTBE should be enough to give a substantial result if theory holds true. A possible issue is the correlation between MTBE bans and states with high crop yields. Many of the states that banned MTBE were in the top ten corn producing states. Another possible issue is that 8 out of the 13 states that banned MTBE did so in the year 2004 or after. As a consequence the distinguishing characteristics between MTBE bans, and the stacked policies could have become muddled. This would lead to the coefficients of STACKED soaking up the positive impact of MTBE, while the coefficient of MTBE was left describing the correlation between the states' policy and prices. However, when MTBE is the sole policy variable, its influence on crop prices is still statistically insignificant. Therefore, the suggestion is that MTBE has no real effect on the prices of corn or its substitutes.

An alternative hypothesis is that the impact of MTBE bans is not significant enough to cause any positive impact on crop prices. According to the EIA (2003), in 2000, over 1.6 billion gallons of MTBE were used by states included in this study before they passed bans[9]. This is equivalent to the amount of ethanol produced in the year 2000 (RFAa). It seems that because ethanol is the main substitute, there should have been a substantial increase ethanol production once the bans were in place. This would be true if the ban on MTBE created enough of an extra demand that it influenced the supply for ethanol.

The most likely reason MTBE bans have no statistically significant effect is because the RFS consumption quota is more than double the amount of ethanol needed to replace MTBE, thus the added demand was not sufficient enough. There are two options for the use of ethanol as fuel once it is produced. It is either used for E85 fuel, which is 85 percent ethanol, or it is used as

[9] Overall, 2.08 billion gallons were used by states that enacted bans, but two major consumers are not included in this study.

an additive, which usually replaces other oxygenates. The demand for E85 is represented by the proxy variable FLEX, which holds no statistical significance in any of the regression models. This implies that the demand of E85 is not large enough to increase the supply of ethanol, and it can be inferred that the majority of the ethanol production is supported by the demand for blending. However, placing a consumption quota above equilibrium demand is similar to creating an inelastic demand curve at the desired amount. By banning MTBE, states are not influencing demand because they are blending ethanol that would have been used anyway. The only difference is that states that ban MTBE blend up to the full 10 percent oxygenate level instead of adding trace amounts to meet the consumption quota.

7. Conclusion

The results of the tests and regressions are somewhat complex. The initial conflict arises with the contradictory results from the Chow test using random-effects models and their subsequent regression results. Even ignoring the initial Chow test, the regression results of the random-effects models did not produce clear outcomes. Re-running the Chow test and regressions for corn and soybeans under new specifications cleared up the issues and produced statistically sound, positive results. Unfortunately, using fixed-effects models contradicts the initial Hausman specification test.

In the end, the results from the fixed-effects model equations for all commodities should be viewed as the most precise results. The reason is that the results of the Hausman test do not lead to a definite specification. Random-effects models are commonly used if the null hypothesis of the Hausman test is rejected for efficiency purposes, but fixed-effects are still credible. Just thinking about the state elements as a clustering variable and the definitions of fixed- and random-effects models, fixed-effects seem to make the most sense. The intercept term for each state should differ depending on the states characteristics, which are not accounted for in the random-effects models. Using fixed-effects actually seems necessary to account for random variances across states such as region, soil quality, disease, etc. Therefore, the results for wheat in Table 7, and corn and soybeans' results in Table 8 should be taken as final.

Analyzing the results for the three commodities under the fixed-effects specification, the influence of STACKED on all commodities' prices is analogous to the theory. Corn prices are by far the most influenced because they are directly affected by the increase in ethanol demand. Wheat and soybean prices will increase as well, but only through substitution effects. The impact of the policy should not fully carry over because there is not a perfect transfer of demand between corn and wheat or soybeans. Instead the effect of STACKED is dampened as it crosses from market to market. Comparing these results to Table 2, one can see that corn experiences the greatest changes in prices from 2005-2008 and soybeans experience the least. The strength of the results is apparent when judging the results against theory and the data.

The size of the coefficients for STACKED is impressive. A 30 percent increase in corn prices, a 9.4 percent increase in wheat prices, and a 6.4 percent increase in soy prices is anything but minuscule. The United States' weighted-average prices for corn, wheat, and soybeans in 2004 were $1.72, $2.84, and $4.79 respectively[10]. By 2008, these prices jumped to $2.23, $3.89, and $5.29. If one were to discount these commodity prices by the estimated influence of the VEETC and RFS, then the 2008 prices would be $1.72 for corn, $3.55 for wheat, and $4.97 for soybeans. Omitting the influence of the stacked ethanol polices brings the prices of the 2008 commodities much closer to their 2004 values holding all other variables constant. The most

[10] Prices are calculated using chained 2000 dollars.

shocking results are that corn prices would not have increased from 2004 to 2008 if the VEETC and RFS were not implemented, all else equal.

These staggering results lead to the question of what is best for social welfare. It is apparent that the ethanol policies raise crop prices through indirect and substitution effects, and these are only the initial impacts on food prices. Corn, wheat, and soybeans are major input crops for many different food commodities. The rising crop prices imply that the ethanol policies also effect common food goods, such as bread and cereal, which millions of people buy from the grocery store everyday. Looking at the price consequences of implementing ethanol policies, they seem too costly, yet the VEETC and RFS have been extended. The reason is that ethanol polices do have a benefit.

The consumption of ethanol has grown each year since the implementation of the RFS. It is not rational to assume that ethanol production grew by roughly 9 billion gallons from 2000 to 2009 and oil consumption was not affected (RFAa, 2009). There are many debates as to whether or not ethanol has environmental benefits over refined gasoline, but it is hard to argue the benefits of becoming less reliant on foreign energy sources. The new version of the RFS sets the consumption quota at 36 billion gallons of ethanol by 2022 (RFAb, 2009). If the consumption quota is met, then it would replace a substantial amount of foreign oil imports. The environmental benefits could also be realized through less offshore drilling and gateway effects towards other, cleaner alternative fuels.

The point of this study is to analyze one of the costs associated with ethanol policies, not to determine if the stacked policies are cost effective. There is however, plenty of room for future research. As more and more data becomes available, the analysis of this topic will explode, but for now it is still a relatively new area of study. The time span of the data used in this study only extended three years after the policy implementations, which is not sufficient to draw long-run conclusions. The true test of the impact of ethanol policies on crop prices will come five or ten years from now when a considerable amount of time has passed and markets have had time to adjust.

This type of study is very versatile because it can be applied on the state level, aggregate level, or through the use of panel data in the future. There is also the potential of extending the study to different commodities that could experience effects through substitutions or inputs, or find a way to model other ethanol policies such as the tariff. This paper is only one of many that will take place on the ethanol policy and food prices. As discussed above there are many pros and cons to supporting ethanol's growth through policies, but long-run effects are still uncertain. Currently, this is still the early stages of the ethanol industry, and only time will tell whether or not the policies are efficient.

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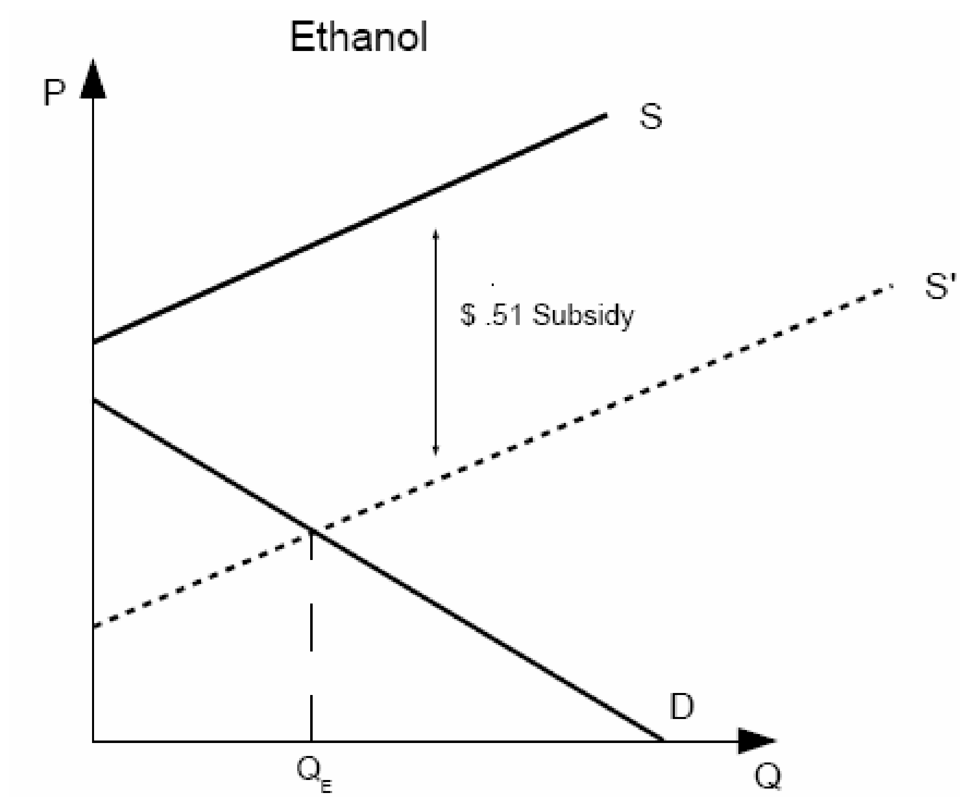
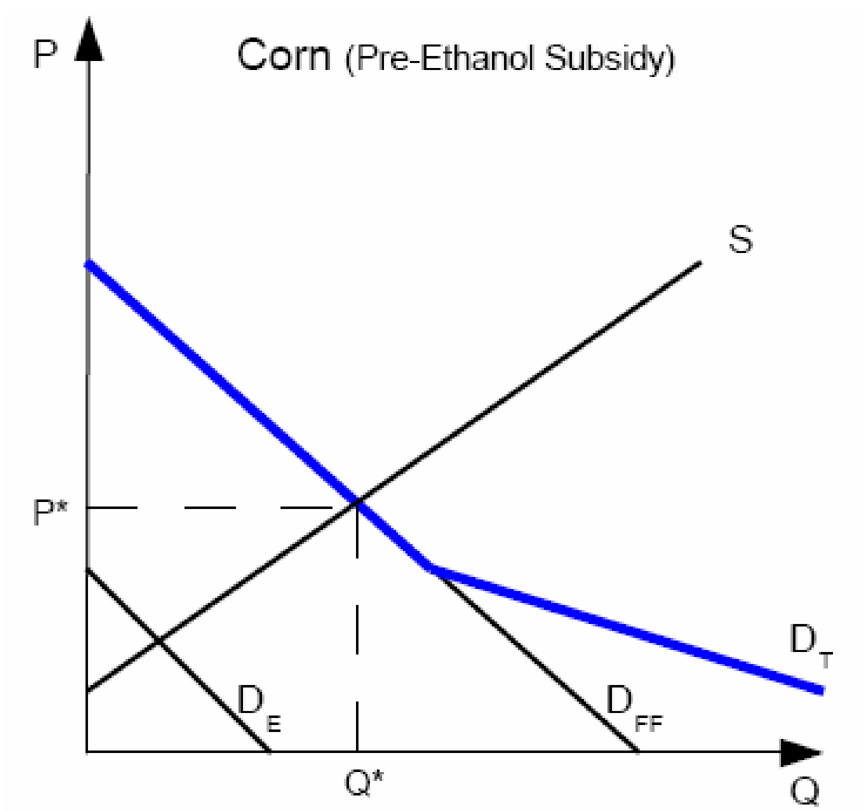
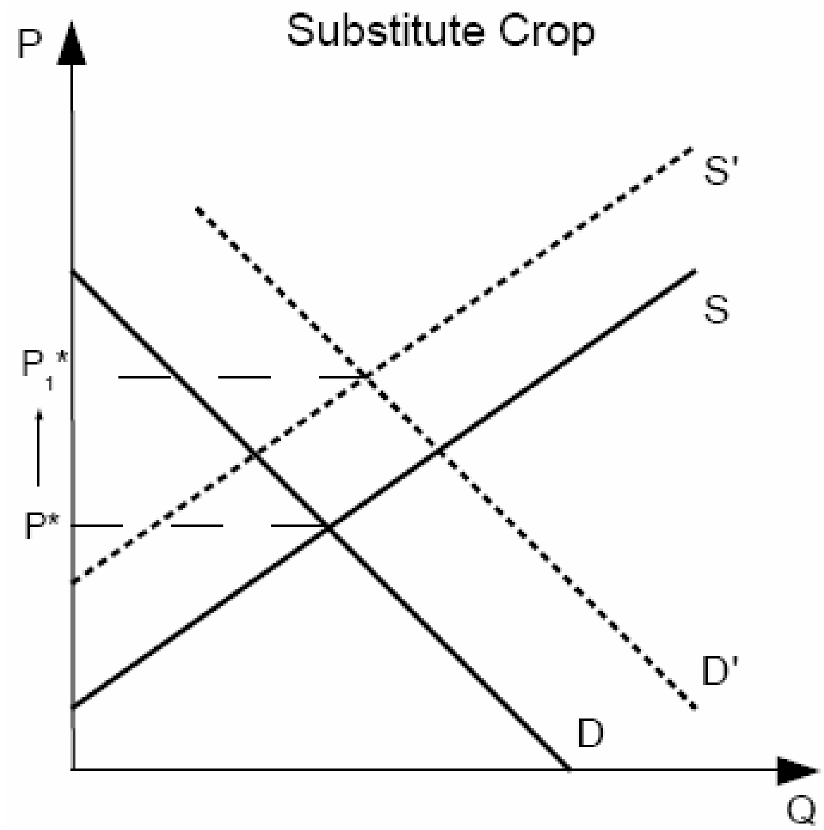
Appendix 1

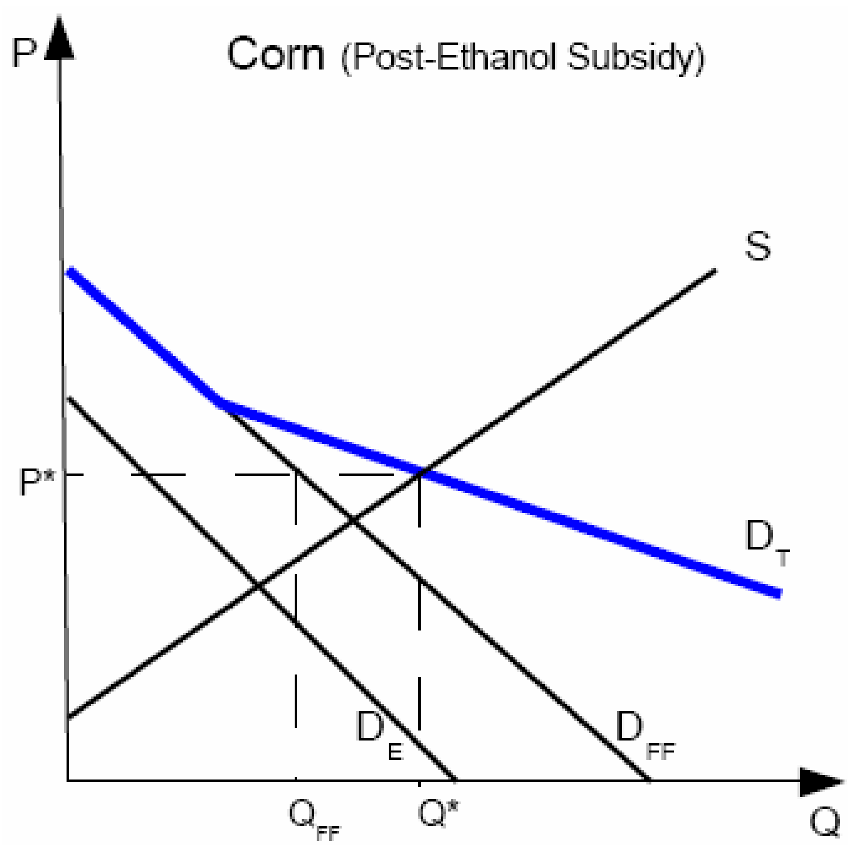


Ethanol
P
S
S'
$ .51 Subsidy
D
Q
E
Q



P
Corn (Pre-Ethanol Subsidy)
S
P*
D
T
D
E
D
FF
Q*
Q


Substitute Crop
P
S'
S
P_1*
P*
D'
D
Q


Corn (Post-Ethanol Subsidy)
P
S
P*
D_T
D_E
D_{FF}
Q_{FF}
Q*
Q

Appendix 2

Variable	Variable Name	Units	Where Collected
Price	lnPRICE(X)	Indexed 2000 Dollars	NASS-USDA
VEETC/RFS	STACKED	Dummy Variable	RFA
MTBE ban	MTBE	Dummy Variable	RFA
Interaction Term	INTERACT	Dummy Variable	NA
Planted Acreage	PLANT ACRE	Thousand Acres	NASS-USDA
Flex Fuel Pumps	FLEX	Number of Pumps	US DOE
Cattle	CATTLE	Thousand Heads	NASS-USDA
Hogs	HOGS	Thousand Heads	NASS-USDA
Chickens	CHICKENS	Thousand Heads	NASS-USDA
GDP per Capita	lnGDP/CAP	Chained 2000 dollars	BEA
Gasoline Prices	lnGAS	Chained 2000 dollars per barrel	EIA

Appendix 3

Figure 6a – Corn Price, 2000-2008

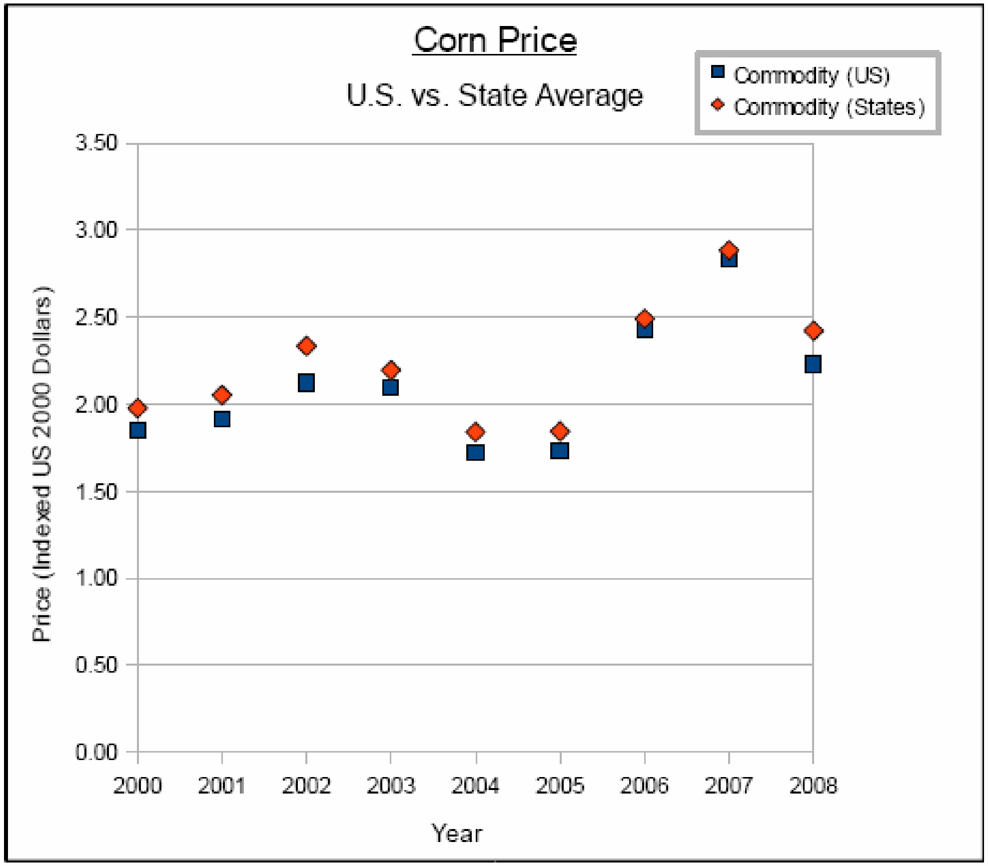


Figure 6b – Corn Yields, 2000-2008

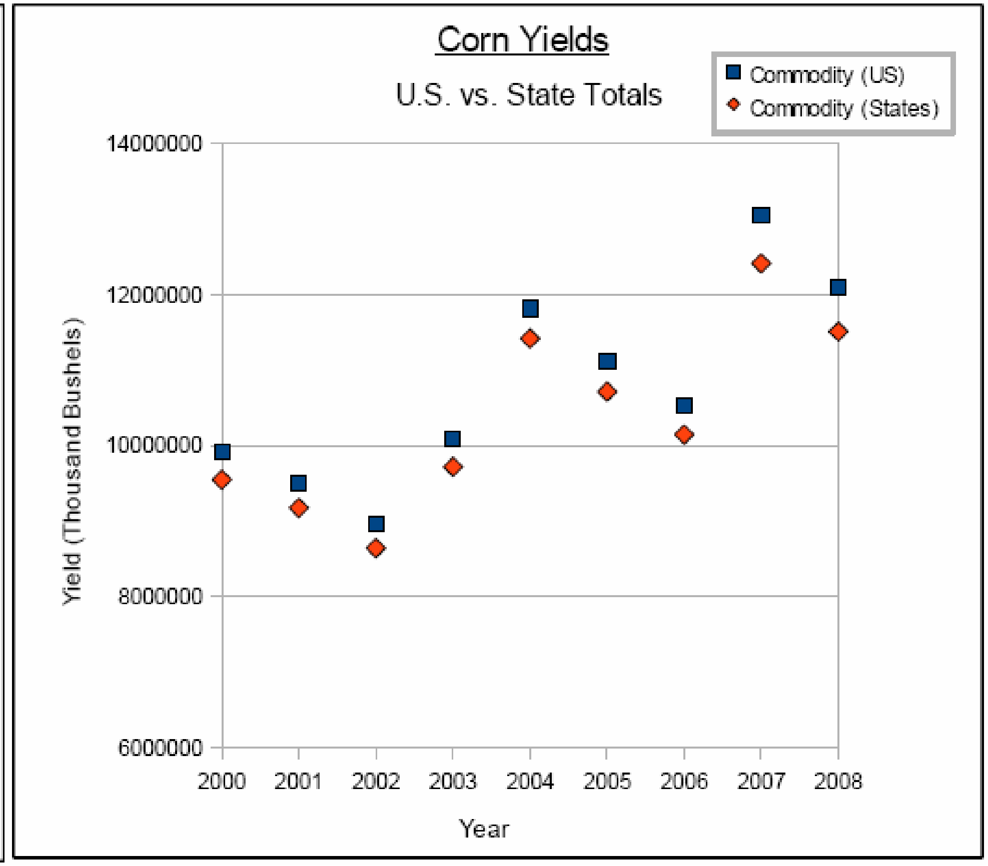


Figure 7a – Wheat Price, 2000-2008

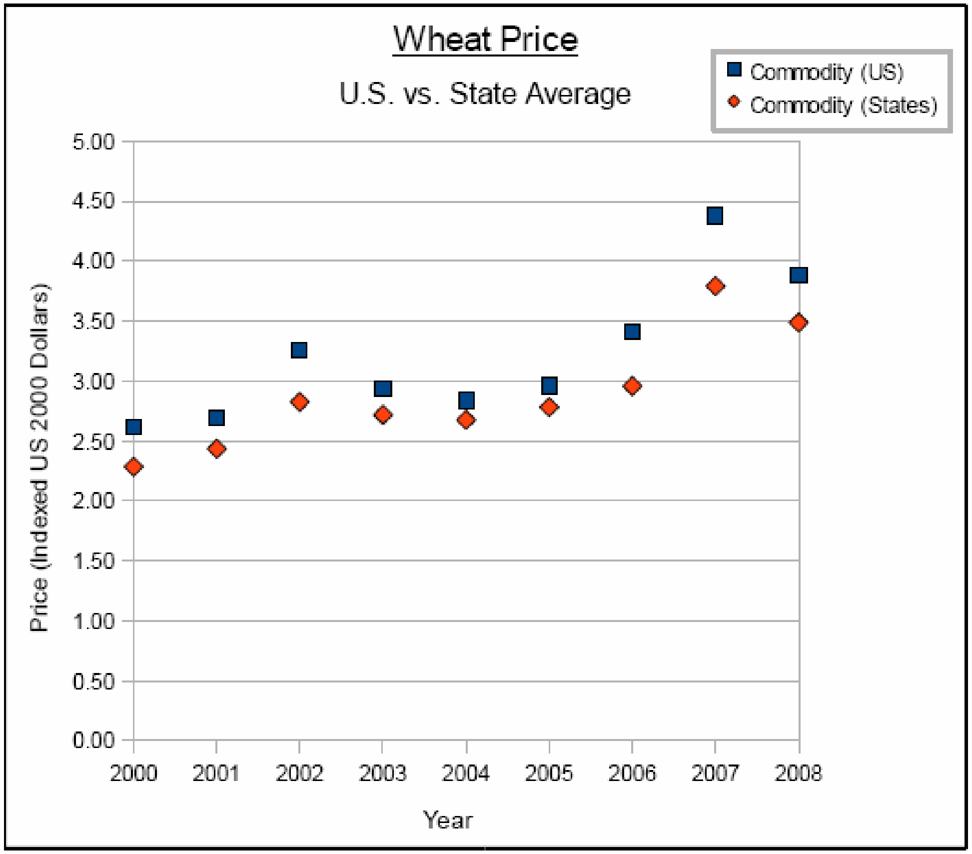


Figure 7b – Wheat Yields, 2000-2008

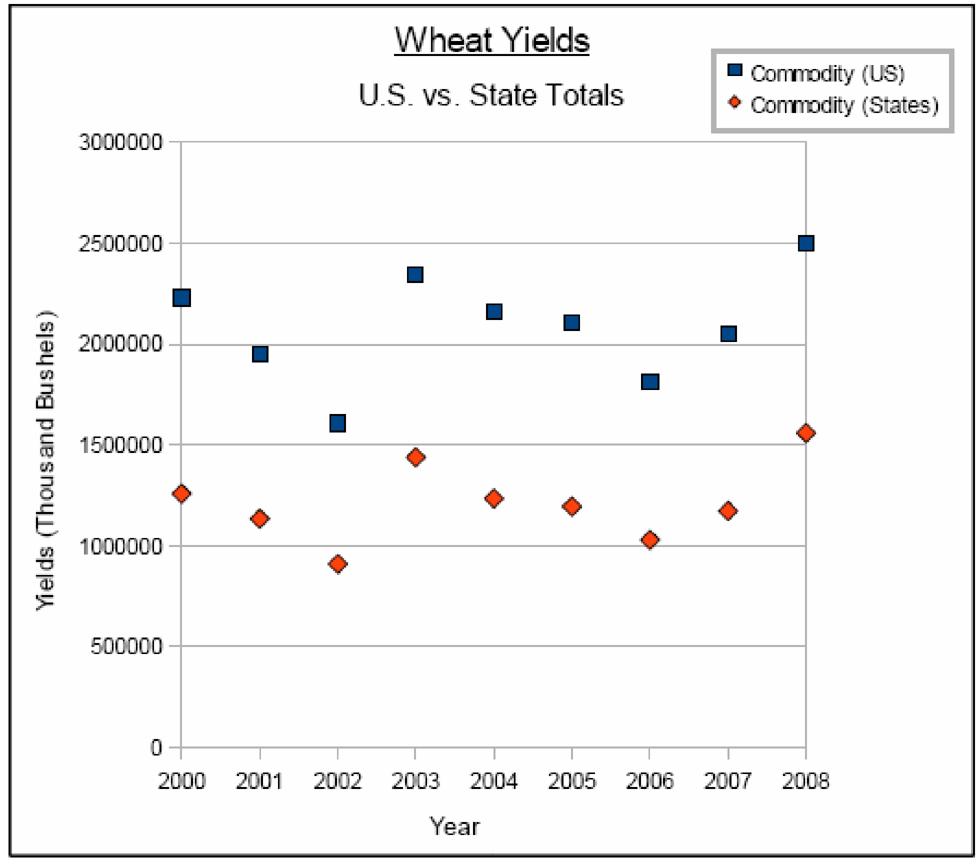


Figure 8a – Soybean Price, 2000-2008

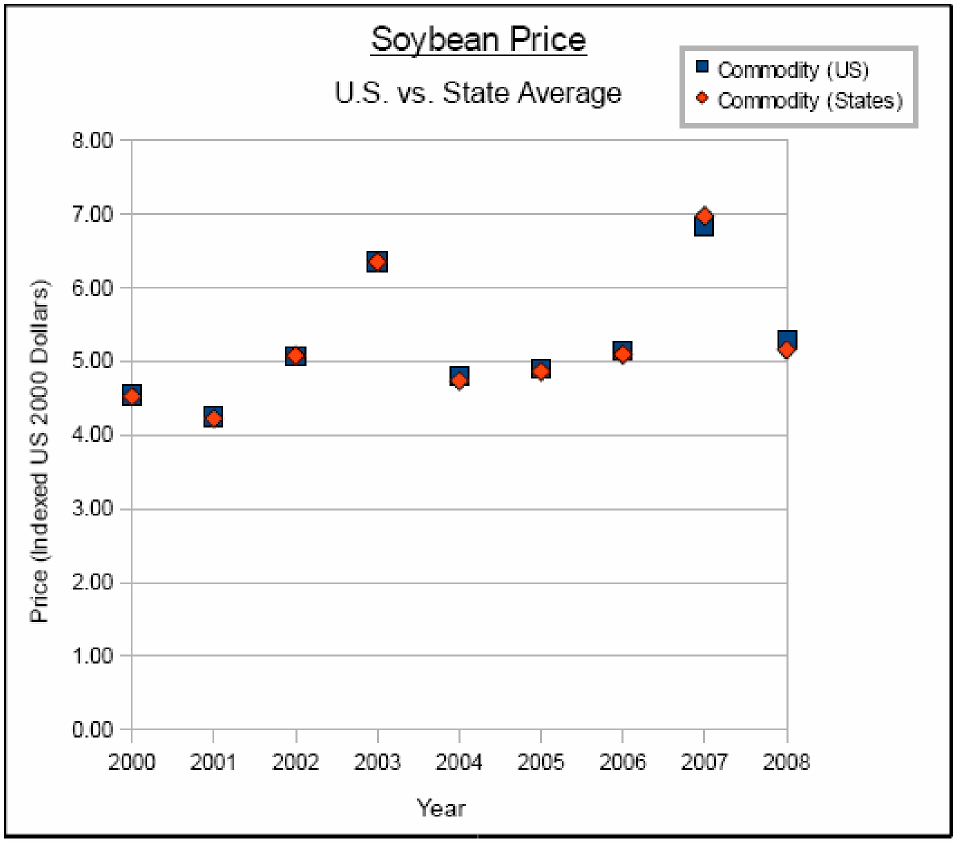


Figure 8b – Soybean Yields, 2000-2008