PRIVATE SECTOR INNOVATION IN BIOFUELS IN THE UNITED STATES: INDUCED BY PRICES OR POLICIES

by

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ABSTRACT

PRIVATE SECTOR INNOVATION IN BIOFUELS IN THE UNITED STATES: INDUCED BY PRICES OR POLICIES

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It has been shown in recent years that high energy prices induce investments in energy research. $100/barrel oil, strategic concerns, concerns about global warming, and pork barrel politics has also rekindled the enthusiasm of the public and government for policies that encourage research and innovation on biofuels. We look at the biofuels supply chain to identify which components of that chain are conducting biofuel research and how prices and policies might stimulate research and innovation. This paper is a first attempt to develop an econometric model to measure how innovations as measured by ethanol related patents have responded to high oil prices and to government policies. We look at the both demand-side factors such as federal policies subsidizing ethanol production or mandates for the use of biofuel and supply-side factors such as government funding for biofuel research. We find that both oil prices and federal research grants have significant positive effects on innovation. However, the size of the ethanol market has a negative effect as do federal tax credits, with mandates being insignificant.

Acknowledgements

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CHAPTER 1: Introduction

The recent rise in the world crude oil prices has not only affected energy and fuel prices but its effects have been seen in food and land prices across the world, making it a global issue of utmost importance. The growing concerns about the limited supply of fossil fuel in tandem with environmental pollution issues have driven the need for alternative fuels that have superior environmental benefits and are economically competitive with fossil fuel.

The energy crisis of the 70's paved the way for the search for an alternative fuel though it was only at the turn of the century that this quest gained momentum. This was at a time when the limited supply of fossil energy became evident and the dependency on the volatile Middle-East energy market became a threat to national security. Also, concerns of the scientific community about global warming due to anthropogenic emissions added to the urgency of research on alternative, renewable sources of energy that would not deplete natural resources.

Whereas solar, hydroelectric and wind energy gained visibility as the new forms of energy replacing coal and oil; in the transportation sector, ethanol and biodiesel emerged as the main substitutes for gasoline and diesel respectively. Since the US is the world's largest consumer of gasoline, the substitute fuel needs to be abundant in supply in addition to being sustainable in the long run. Ethanol from corn is an established product, being widely used in the alcohol industry and in the chemical industry as a solvent. Therefore, corn ethanol gained much attention from the public and private sector with the result that it has become rapidly absorbed in the automotive industry as a fuel blend. In recent years, research on alternatives to corn as the prime source of ethanol is getting a lot of attention.

The primary objective of this thesis is to understand how biofuels research is responding to high oil prices and government policies. We need to first identify the primary areas of research in biofuels and analyze the effects of the various factors on the amount and direction of private biofuel R&D. In order to do this, we look at the major players in biofuels production and research, the markets and their size across the supply chain. Then we identify the determinants of private R&D investments and quantify, when possible, their significance. In doing so, we aim to further our knowledge of where the concentration of R&D in biofuels is and how that is fulfilling the goals of energy independence and reduced GHG emissions.

The thesis is organized as follows. First, we look at the background on the how the biofuel industry evolved and what factors have created the demand for the ethanol industry. We describe the ethanol supply chain for better understanding of the key areas of research and the major players in the industry. We then look at the existing literature on the determinants of private sector R&D, and the role of public institutions determining these investments. In the conceptual framework, we develop the analytical model for private R&D and describe in detail the explanatory variables. The data modeling and results section describes the sources of data and the algorithm used to fit the data to the desired model. Finally, we discuss the quantitative results and derive policy implications. We attempt to make some recommendations for the direction of future research in this field.

CHAPTER 2: Background

In this section, we describe the biofuel industry and the ethanol and biodiesel production processes with the goal that it will provide better understanding of the different components of the biofuel (specifically ethanol) supply chain explained thereafter. Since our focus is on private sector contributions, we look at the kinds of R&D investments by private companies and indentify the major players in the ethanol industry.

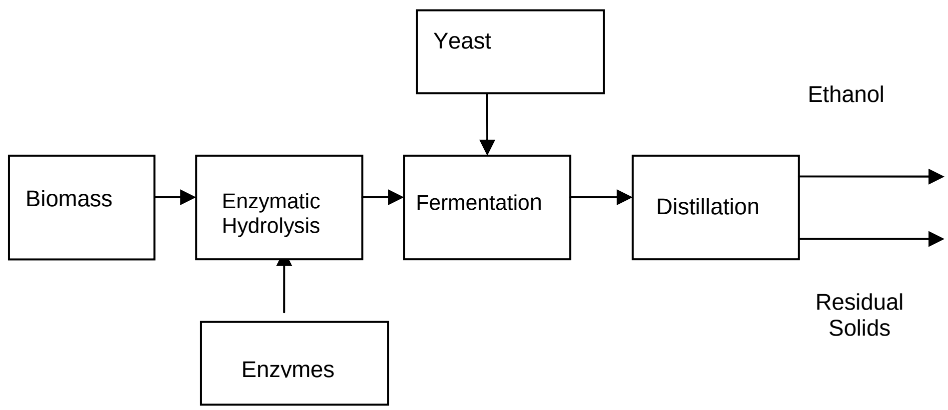
Biofuels Industry

Ethanol and biodiesel are established products in the industry. Ethanol has been used as alcohol for centuries and more recently as an industrial solvent. It was in early twentieth century that Rudolf Diesel used peanut oil to run his first diesel engine. Although ethanol and diesel can be made from petroleum, they can also be renewable fuels if the inputs used to make them are different kinds of biomass or plant material.

Bioethanol

Bio-ethanol is obtained from the conversion of carbon based feedstock as shown in Figure 1. The major steps of the production process include: feedstock production, harvesting, and collection, feedstock storage and preparation, pretreatment, ethanol fermentation, and ethanol recovery. The biomass feedstock, such as corn, wheat or barley straw, is first milled and cleaned in the preparation stage. In case of cellulosic biomass, there is an additional stage of enzymatic hydrolysis in which the pretreated biomass is digested by enzymes to release sugars. These sugars are then fermented by yeast to yield ethanol and carbon dioxide. Ethanol is recovered in the distillation process, and the fermentation residue is processed further for use as animal feed or to recover useful chemicals.

Figure 1. Ethanol Production Process

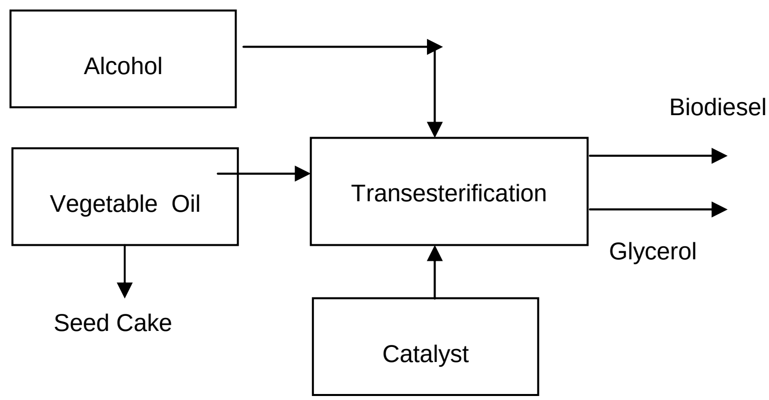


Source: Renewable Fuels Association (RFA)

Biodiesel

Biodiesel is a term applied to esters of naturally-occurring glycerides such as vegetable oils. It is produced by chemically reacting a fat or oil with an alcohol such as methanol, in the presence of a hydroxide catalyst like sodium or potassium hydroxide (Van Gerpen 2005), a process known as *transesterification*. The product of the reaction is a mixture of methyl esters, which are known as *biodiesel*, and glycerol, which is a high value co-product. Common feedstocks for biodiesel are vegetable oils such as soybean, castor and rapeseed. The extrusion of oil from the oil seeds produces seed cake as a byproduct which is very useful as animal feed.

Figure 2.Biodiesel Production Process

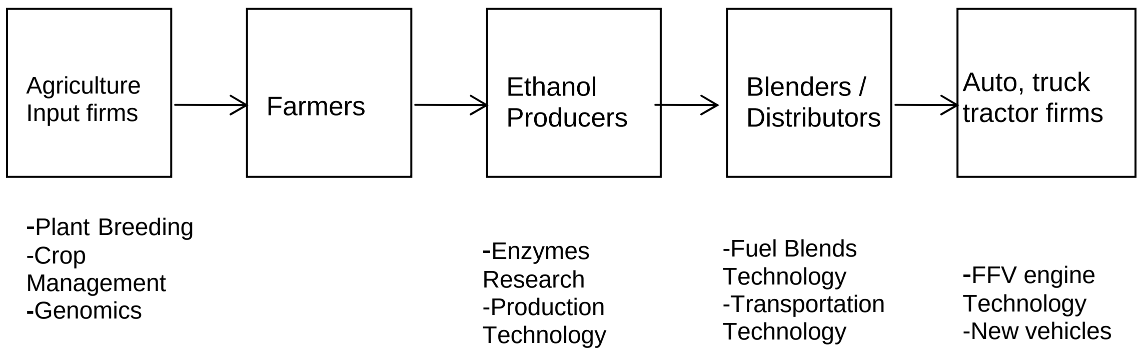


Source: National Biodiesel Association

Private Sector Research in Biofuels

In an attempt to understand the kinds of research being undertaken by the private sector, we first describe the ethanol industry supply chain shown in Figure 3.

Figure 3. Ethanol Industry Supply Chain with types of research conduct

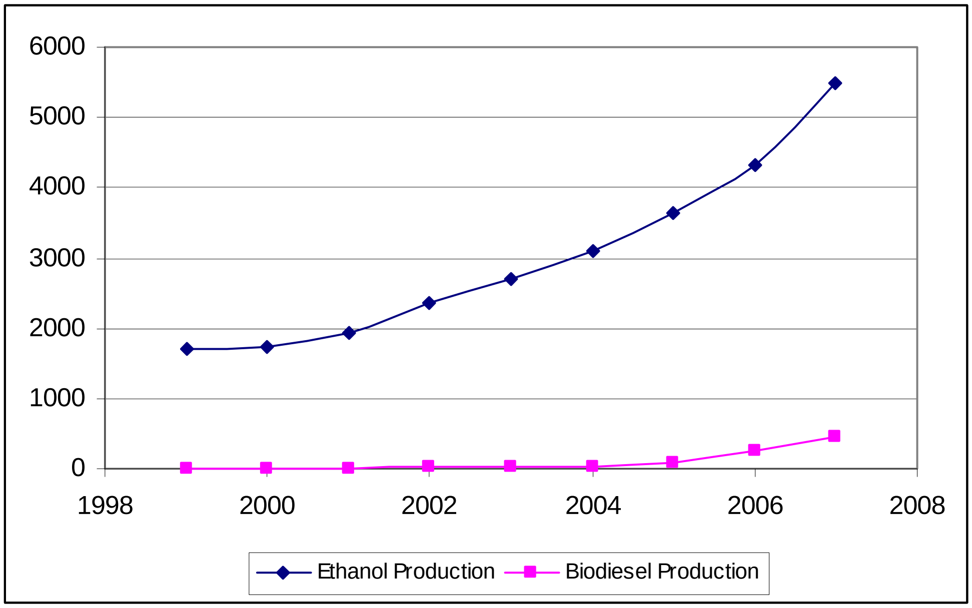


The first set of players contributing to biofuel research are the agricultural input firms companies studying biofuel crops such as biotech firms and seed companies that are finding new crops or new varieties of existing crops with optimum energy content. In the past decade, several small biotech firms are doing research on new crops, new varieties of biofuel crops that would have higher lingo-cellulosic content and less undesirable traits for optimum energy content. For example, Ceres Inc. is looking at higher yield switchgrass varieties whereas Edenspace Corporation is developing commercial corn hybrids for low-cost conversion to ethanol (BRDI 2007). Major seed companies such as Monsanto and Syngenta are seeing profitability in the biofuel crop market and have shifted R&D resources to screen their elite corn lines and developed hybrids that can produce more ethanol per acre as well as developing varieties of the new energy crops.

The next component of the biofuel supply chain is the farmers who produce the corn, biomass, soybean etc. This raw material is then converted to ethanol or biodiesel by ethanol producers. Many of these producing firms are owned by farmers who have formed cooperatives which invest in biofuel plants to take collective advantage of the increasing demand for biofuels.

Production of ethanol (called biorefineries) in the US is mostly done in the private sector by major agribusinesses or chemical companies with certain agricultural or manufacturing infrastructure in place. Archer Daniels Midland, POET energy and VeraSun Energy are the 3 major US producers with a combined production of 30% of total ethanol production (RFA). There are also locally-owned companies which are either wholly or partially owned by farmers or cooperatives such as Glacier Lakes Energy, SD and Absolute Energy, IA which produce about 100 million gallons a year each. Figure 4 shows the annual production of ethanol in the US, which has increased dramatically from 2005, with a net 41% increase in number of ethanol plants in the since 2000. Also on the same graph is the biodiesel production which has not caught on as much as ethanol but shows a sharp increase from 2005.

Figure 4 Biodiesel & Ethanol Production in the US (million gallons per year)
Source:RFA & National Biodiesel Board



Enzymes are an important input into the bioethanol conversion process as the complex carbohydrates in the biomass need to be broken down into simpler sugars which can be then fermented to produce ethanol as a by-product (Sheehan & Himmel 1999). The critical difference between feedstock conversion technologies is the enzyme used to treat the biomass since using the right enzymes based on the feedstock is crucial to obtaining energy efficient ethanol at the end of the process. Diversa, an enzyme company which became a part of Verenium in 2007, has identified millions of microbial genomes from which enzymes can be tailored for any feedstock. Commercialization of cellulose ethanol from wheat straw has been successfully demonstrated by Iogen Inc. with a 10 million gallons a year capacity, the first of its kind in Canada. In the US, Verenium will build a 1.4 million gallon demonstration plant from bagasse – the fiber that is left after all the juice is extracted from sugarcane, in Lousiana (Krupp 2008).

The next component in the supply chain comprises oil refiners and blenders who mix gasoline with the required percentage of ethanol, as dictated by mandates, for sale at the pump. Many states in the US have a mandate of 10% ethanol blended with gasoline. Petroleum companies such as Royal Dutch/Shell, Conoco-Phillips and BP are doing research on the effects of different ethanol blends on engine performance. At the end, we have consumers who fill up their cars with the blended gasoline or gasohol. Car manufacturers such as Ford and Chevrolet and tractor manufacturers such as John Deere have shifted their research and engineering budgets to develop modified engines to accommodate the properties of the new fuel blend. Flexible Fuel Vehicles (FFV) have engines that can operate with either ethanol blended gasoline or 100% ethanol.

Table 1 gives some indicators of research across the ethanol supply chain. The types of research and major companies have been described above. The government agencies, Department of Energy (DOE) and United States Department of Agriculture (USDA) formed the Joint Biomass R&D Initiative (BRDI) in 2000 to provide financial incentives to public and private institutions for R&D in biofuels. In the past years, DOE has mainly supported research in biomass-to-biofuels processing and conversion technologies as is evident from some of the early advances in enzymes research. The BRDI, under which each agency takes individual responsibility for projects, mainly focuses on 'plant science research' and 'biorefinery demonstration and deployment' type of projects, in addition to feasibility studies on next generation technologies such as synfuels. As can be seen from the table, the total funds granted by the DOE from 2002-

2006 was about $130 million, of which 71% went to biofuel producers. USDA has contributed $30 million over the same period, with 41% to ethanol producing companies. In many cases, private firms have to match a portion of the amount of the grant. For example, in 2007, BRDI solicitations required firms to match 20% of the grant money for research projects and up to 50% for demonstration projects.

Next we look at the patenting activity by private firms and find that most of the patents, about 90%, are in enzymes research followed by firms studying effects of higher ratios of ethanol on engine performance. Among the top enzymes companies, Genencor and Novozymes hold 60% of the number of patents (Clark 2008). So far most of the patenting was done by private companies who receive little federal funding and who rely mostly on in-house research investments.

Table 1: Research across the Ethanol Supply Chain

	Ag inputs	**Ethanol inputs**	**Ethanol producers**	**Distributors /blenders**	**Auto & tractor firms**
Type of research	Plant Breeding, Genomics, Crop management	Enzymes research, Processing and conversion	Engineering, Improved production, Technology	Fuel Blend Technology, Improving distribution	Develop engines that can run on biofuels
Firms doing research	Biotech, lumber companies e.g. Mendel, Pioneer Hybrid, Syngenta	Biotech e.g. Novozymes, Ceres, Genencor	Manufacturing companies Abengoa, ADM, Cargill	Oil companies e.g. Chevron, Texaco, Shell	John Deere, Daimler, Ford, General motors, Volkswagen
DOE[n] grants to private companies (2002-2006)	$ 10.7 million	$ 25.2 million	$93.4 million		
USDA[n] grants ($) to private companies (2002-2006)	$ 6.9 million	$ 13.6 million	$ 14.7 million		
Universities	Land grant institutions, State Universities Illinois, Iowa State, Michigan State	Public and Private universities, DOE National Labs e.g. Penn State, Princeton University, Argonne National Lab	Land Grant Universities, Experiment Stations e.g. Purdue, Washington State University, Texas Ag Experiment Station	Private Universities e.g. MIT, Princeton University	
Number of Ethanol-related Patents	4 0.1%**	400 89.8%	9 2%	36 8%	
Market size in 2007	4.8 billion* bushels corn @ $4/bushel=$192 million	Private R&D expenditures	6.8 billion gallons ($2.64/gal) = $17.95 billion		

* 37% of yield of 13.3 billion bushels in 2007
**Of total patents found on USPTO
n Source: Joint Biomass R&D Initiative, DOE (2008)

CHAPTER 3: Literature Review

The inception of biofuels was a response to the quest of alternative fuels in the wake of rising oil prices and imminent scarcity of oil supply. Thus the biofuel movement was essentially induced by these factors. The past literature on induced innovation and results of some recent studies on effects of prices on innovation are presented in this section.

The 'induced innovation hypothesis' was first introduced by Sir John Hicks in 1932. He argued that a change in relative prices of factors of production sets the stage for invention, which is directed to economizing the use of the factor which has become relatively expensive (Hicks 1932). Schumpeter (1942) noted that the process of invention and innovation are carried out primarily by private firms and are collectively called research and development. In the 1960s, the theory of induced innovation gained importance in the literature on economic growth. A train of thought put forth by Schmookler (1966) and Griliches (1957) focused on the relationship between technical change and product demand and concluded that changes in product demand and relative factor prices are inseparable in the process of economic development, since changes in one inevitably result in changes in the other. To put this argument in proper perspective, Hayami and Ruttan (1985) suggested a more general equilibrium theory of induced innovation in which changes in both product demand and relative factor prices, determine the rate and direction of technical change. They applied these ideas to agriculture and showed that a relative scarcity of labor would result in substitution by land and capital, made possible by technical advances in machinery that would facilitate production. The constraints to agricultural development created by an inelastic supply of labor could lead to advances in mechanical technology, such as new harvesting machinery, whereas those created by inelasticity of land could lead to changes in biological technology such as better fertilizers that can increase yield per hectare.

A production possibility frontier describes a set of inputs and outputs that are technically feasible at a time. Jaffe (2001) explained that technological change can be measured by the movement of this frontier due to output vectors that were not previously feasible. The following relationship describes the production function of an industry

$$Y = f(K,L,t) \quad \ldots\ldots \quad (1)$$

Where Y is the aggregate output, K and L are capital goods and t is the time. A technological change would mean that the relationship between inputs and possible output levels changes. Thus logarithmic differentiation of the above equation results yields

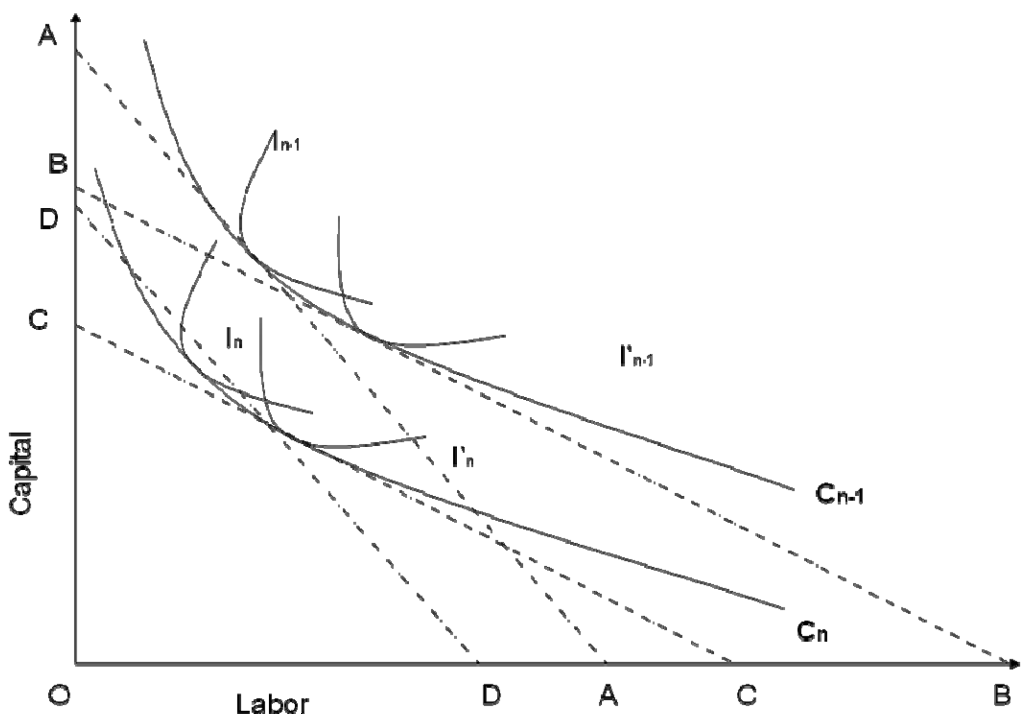
$$Y_t = A_t + B_{Kt}L_t + B_{Kt}K_t \quad \ldots\ldots \quad (2)$$

We see here that the term A_t corresponds to 'neutral' technological change since it represents changes in output when the rate of change of inputs is zero, whereas the B's relate to 'biased' technological change i.e. relative changes in the inputs over time.

We present here, Syed Ahmad's model of induced technical innovation which introduces the Innovation Possibility Curve (IPC) in a specific time period. This is shown in Figure 5 by C_n and C_{n-1}, which is an envelope of all the alternative isoquants- I_{n-1}, I'_{n-1} (representing a given output on various production functions) corresponding to the alternative technologies that can be potentially developed for a given research budget at a given time.

It should be noted that the act of invention takes us from one production function I_{n-1} to the other, I'_{n-1}, whereas factor-substitution takes us along the same production function. The tangent AA to the production function I_{n-1} represents the budget or the constraint line that minimizes the cost of production with a relative price of labor and capital. If an invention takes place in response to change in relative price of say capital, then we can move to a different production function I'_{n-1}, which is more capital-saving as indicated by the budget line BB.

Figure 5: Ahmad's Innovation Possibility Curve



Syed Ahmad defines neutrality of the innovation possibility that could be caused by increase in product demand, as the situation in which innovation C_n in response to any relative factor price at time n, is neutral to the innovation C_{n-1} in response to same relative factor price at time n-1. Therefore, I'_n and I'_{n-1} are neutral innovations in response to the same relative factor price ratio whereas, along the IPC at a later time period n, DD would induce be more labor saving innovations than CC. So, if at time n, there is a rise in relative price of labor, then the isoquant I_n will be chosen as it is more labor-saving.

Popp's (2001a) work on relationship between electricity prices and innovation which is also based on the induced innovation theory serves as the main basis of our empirical model. Popp considered patents in 11 energy-saving technologies in the US such as solar, wind, biomass, as a measure of innovation. He used patent citations to measure technological opportunity for future R&D and energy prices as a driver of market demand and using these as determinants of innovation, he found that patenting activity increases in response to increase in energy prices, with the most effect occurring within first few years and then fading over time due to diminishing returns to R&D. He also found that government-sponsored R&D had little effect on private energy patenting.

In a more recent study by Popp and colleagues (Johnstone et al 2008), patent counts have been used to measure the effect of different government policies in renewable energy such as tariffs and quotas, on technological innovation. The authors use panel data from 25 OECD countries and 26 years and conclude that public policy does play a significant role in inducing innovations; however the efficacy depends on the type of renewable source. They found that overall, in biomass energy, government investment incentives such as grants and mandates have negative but significant effect whereas tax credits has a positive and significant effect. Another study by Wu et al (2005) examine the role of three major innovation policies (patent protection, R&D tax incentives and government funding) on private aggregate R&D expenditures. The authors use OECD data for nine countries from 1985-1995 and find that government research grants play a significant role in business R&D expenditures; in fact, a 10% increase in subsidies generates up to 4.1% additional R&D investments. Their results also suggest that tax policies that lower the user cost of R&D, such as tax credits, stimulate private sector R&D expenditures.

Nemet and Kammen (2007) used successful patent applications as a proxy for intensity of inventive activity in the energy sector and conclude that there is a strong correlation between patenting and federal R&D expenditure and so with the decline in R&D budget, patenting in the energy sector showed a declining trend in the late 90's. Their results show that large government R&D initiatives are associated with increased private sector R&D and thus an upward trend in patenting activity.

CHAPTER 4: Conceptual Framework

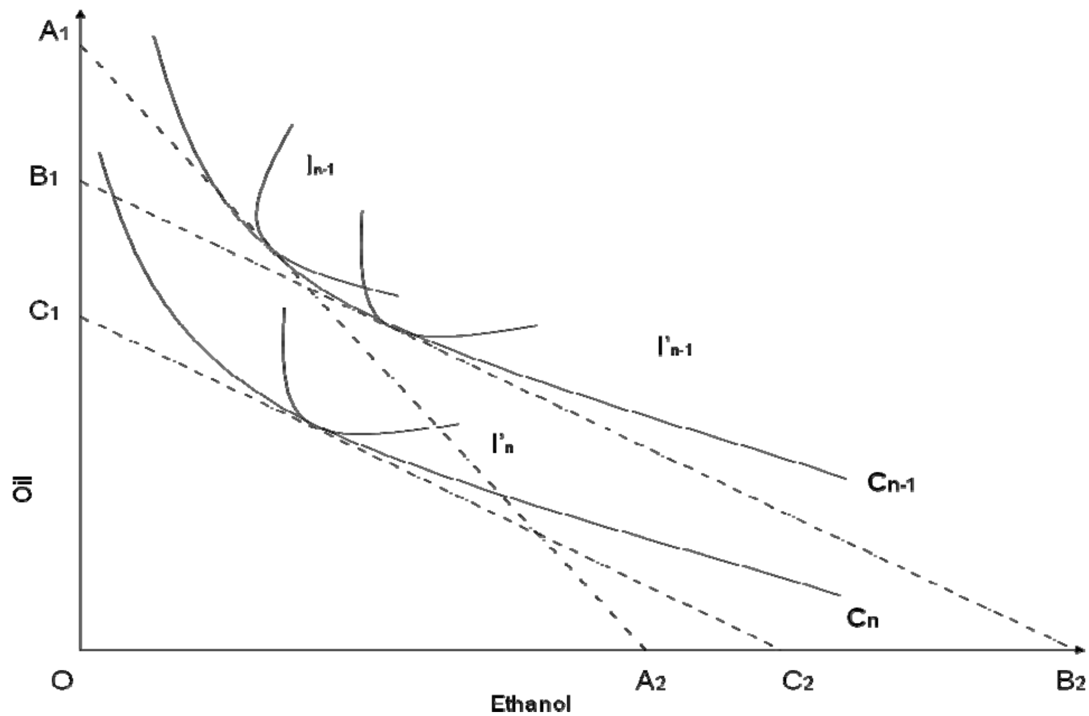
Building on the literature review this section describes the application of theory to our research problem and formulates a model to test our hypotheses.

Induced Innovation in the Biofuels Market

In the transportation fuels market, ethanol is blended with gasoline in different proportions by volume - 5% (E-5), 10% (E10) or 20% (E20) and the mixture is called 'gasohol'. In Figure 5, we apply Ahmad's model towards explaining induced innovation in the liquid fuels market, which we know from our previous discussion was driven by the need for oil-saving technology.

The main player in the gasohol market is the auto manufacturing industry which was needed to come up with gasohol-compatible engines for cars and trucks. In Figure 6, C_{n-1} and C_n are the IPCs at time periods n-1 and n respectively whereas I_{n-1} and I'_{n-1} are the isoquants in time period n-1 and I'_n is the isoquant belonging to C_n. These isoquants represent gasohol production functions at various combinations (or blends) of gasoline and ethanol.

Figure 6: Induced Innovation in the Gasohol Market

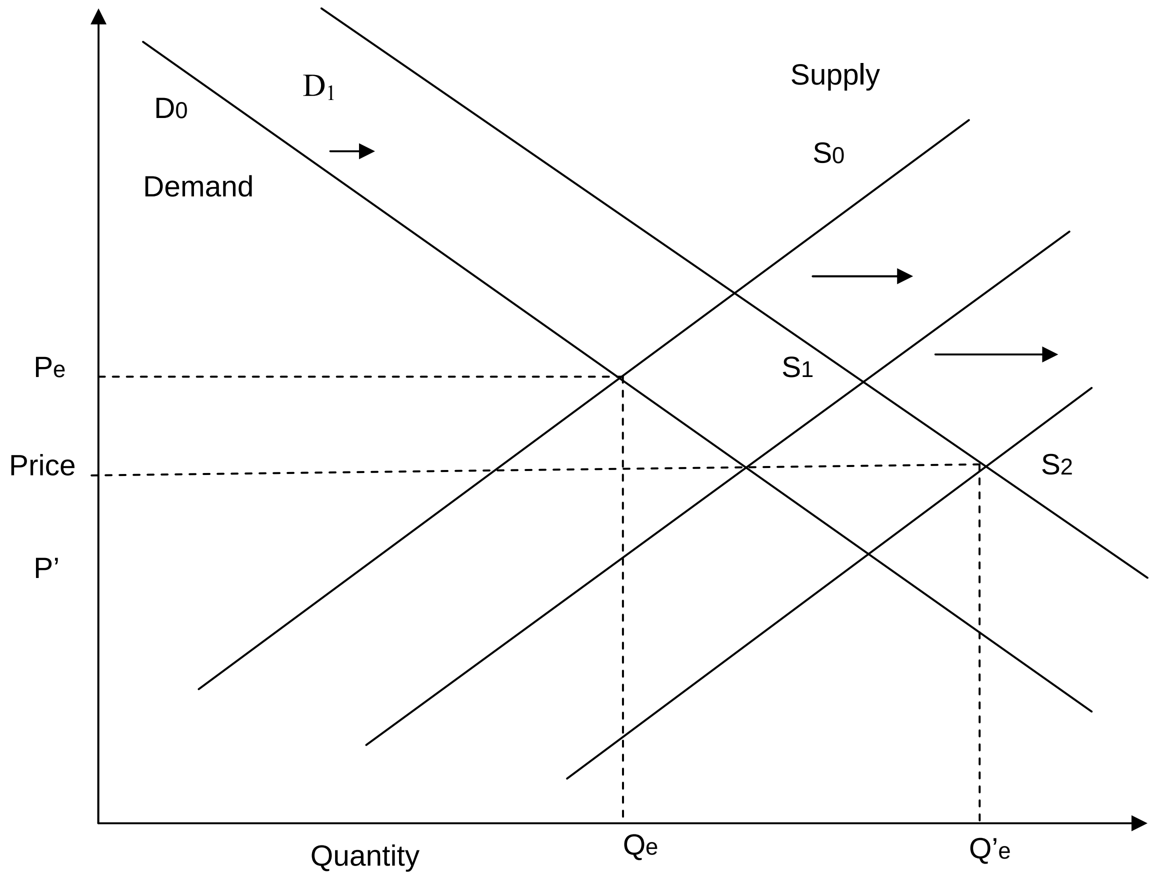


We begin at time n-1 when I_{n-1} is the isoquant representing a particular combination of oil and ethanol. A_1A_2 is the price (or budget) line that is tangent to the IPC and that determines minimum cost of production for the curve I_n-1, given the relative factor prices. This implies a blend ratio of quantity of ethanol to quantity of oil as A_2/A_1 (where A_1 and A_2 are the distances from the origin O) which can be obtained at minimum cost on the production function $I_{n-1.}$ The Alternative Motor Fuels Act of 1988 (AFMA) provided incentives for auto manufacturers to develop and produce more alternative fuel vehicles, in response to the supply instability and rising prices of oil. This led to innovations in alternative or flexi-fuel engines that could run on higher blend ratios and resulted in a movement along the same Innovation Possibility Curve to I'_{n-1}, which is more oil-saving than I_{n-1}, thus rotating the budget line to B_1B_2. However, FFVs were a demand-side induced innovation, which created awareness and market for increased consumption of ethanol. This needed to be matched by expansion of the ethanol supply market that would lead to more refueling stations across the country.

Hans P. Binswanger (1974) deduced in his model that the IPC is induced to shift inwards towards the origin due to the growth in product demand. This is also explained by Ahmad as the neutrality of the innovation possibility curve which means that an innovation at time n-1 is neutral to the relative factor price at time n. Any changes which are not caused by factor prices such as new production practices or discovery of new enzymes, that lead to more cost-efficient gasohol can be attributed to neutral technological change. In our diagram, this means a shift of the IPC to C_n at a later time period n due to exogenous changes, and I'_n is the isoquant at which the tangent price line C_1C_2 is parallel to the B_1B_2. Thus the relative resource saving due to technical change is C_2B_2/OB_2 or C_1B_1/OB_1.

Figure 7 depicts the Ethanol Supply-Demand Curves where D_0 and S_0 are the demand and supply curves respectively. We would like to explain the exogenous changes that cause the shift of IPC downward using the changes in the ethanol market caused by the factors in the supply chain that may not be directly affected by the changes in factor prices. As per our discussion above, rise in oil prices induced changes in engine technology that created a demand for ethanol thus moving the Demand curve to the right from D_0 to D_1.

Figure 7: Ethanol Supply and Demand



With a market demand for ethanol, more firms invest in ethanol-related research leading to improved technology that increases ethanol supply thus shifting Supply curve S_0 outwards to S_1. In recent years, the focus on research on cellulosic biomass in favor of corn as a feedstock for ethanol is leading towards shifting the Supply curve out farther to the right to S_2. This has the effect of increased ethanol production with reduced prices as the new technology matures.

Hypothesis to be tested

To analyze the relationship between prices, government policies, research and innovation, we begin by considering that a firm decides to innovate with the goal of making profits and/or to gain a competitive edge over other firms. Another reason would be to reduce its costs of production which are caused by changes in the relative prices of inputs and leads the firm to find a substitute for the more expensive inputs, according to the induced innovation theory described earlier. In this context, the relative increase in the energy prices (specifically, price of crude oil) is creating a market demand for alternative fuels which is driving R&D in alternative fuel technologies such as ethanol. In recent years the rise in corn prices and the externalities associated with corn ethanol have led to the exploration of different kinds of alternative feedstock such as cellulosic biomass, municipal wastes, wood wastes etc. Thus we would like to use price of corn as a driver of innovation in the ethanol industry.

Another important determinant of private sector innovation has been availability of federal funds to support research (Mansfield, 1981). This would be very relevant in our model due to the recent interest of the government in financing biofuel-related projects. Clean Air Act of 1970s and the more recent Energy Policy Act of 2005 have opened up new opportunities for the private energy industry to invent and innovate in the different areas of energy efficiency and alternative fuels. Popp (2002) has demonstrated the importance of the role of environment policy in inducing innovation in energy-efficient technologies. Since we would like to look at the effects of various government policies on innovation, the last variable in our model would be federal policy towards biofuels. This results in the following outline for our framework for private sector innovation in a particular year as:

Innovation = f(prices, private R&D, federal research funds, federal policy) where federal funds include research grants, awards to the private sector and federal policy is a dummy variable of biofuels-related policies.

Mansfield (1981) has pointed out the difficulties in interpreting R&D expenditures due to the generalized usage of the term which does not differentiate between applied and basic research or long-term and short-term projects, which have different implications. There is also the problem of reporting R&D figures in the private sector which makes it more difficult to obtain data on specific areas such as biofuels R&D.

Since our dependent variable is patent data which would be a discrete, non-negative integer, we use count data method, where the expected value of the count, i.e. number of patents, conditional on a set of explanatory variables, is modeled. The goal is to find how the conditional expectation $E(y|x)$ depends on each covariate , where y is the dependent variable and x is the set of explanatory variables. However, we cannot perform standard linear regression on count data models due to the fact that y is non-negative and discrete and a linear model of the form $E(y|x) = x\beta$ cannot ensure that the predicted or estimated values of y are zero or positive. To overcome this limitation, we model the expected value of y as an exponential of the form $E(y|x) = \exp(x\beta)$, since the value of exponential function is always positive. Since this is a nonlinear relationship, and nonlinear least squares exhibits heteroskedasticity, we use a maximum likelihood model to explain y. Instead of minimizing sum of square residuals in nonlinear linear squares, we find the maximum likelihood that y will take on the expected values. Our count data which cannot have normal distribution, is specified using Poisson distribution which has a constraint that the conditional variance should be equal to the conditional mean i.e. var(y|x) = E(y|x). Since this constraint is too restrictive and violated in many applications, we use the Poisson Quasi-Maximum Likelihood Estimator (QMLE) which uses the robustness of the Poisson distribution but ignores the variance restriction. (Wooldridge 1997). Thus exponential function most commonly used to explain the conditional mean leads us to our model:

$$E(y|x) = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ \beta_k x_k) = \exp(x\beta) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3)$$

where β_k is the coefficient of the explanatory variable x_k. The advantage of this functional form is that if we replace x (assuming x>0) with log(x), then β_k is the elasticity of E(y|x) with respect to x_k.

Even if competitive firms shift their research resources quickly in response to changes in input prices, there will time lag between research investment and actual patent applications, though patent applications are generally made early in the life of a research project (Griliches, 1990). The lag between public funding for research and innovation is likely to be even longer. DOE generally announces grants and after receiving applications, disburses funds to companies based on their past research capabilities. Thus, firms have knowledge of the type of research projects ahead of time and would be better prepared with resources by the time the funds are made available. Therefore we can assume a time lag of 2 years from the time of the award to the date of patent application.

The propensity of a firm to patent can also be a function of the availability of stock of knowledge K. In other words, if there are diminishing returns to the current research, then it might make future R&D more difficult. This concept was not captured in the induced innovation theories which treated existing knowledge stock on which inventors can build upon, as exogenous (Nordhaus, 1973). For example, the discovery of a new enzyme for breaking down complex carbohydrates in switchgrass could pave way for innovations in commercializing the ethanol production process or developing the most suited cultivar for biomass conversion. We include another factor that would encourage firms to innovate and that is the market demand for ethanol as a fuel alternative, which can be measured using past information of the ethanol market size. Finally, due to the fact that many economic time series have a tendency to grow over time, we add linear and quadratic time trend variables T and T2. This avoids false conclusions that sequences appear to be correlated because they both trend over time. The sequences could be moving together not because changes in one are caused by changes in the other, but because they are trending over time due to other unobserved factors.

We can now arrive at our estimation framework as shown in Equation 4.

$$bio\_pat_t = \exp(\beta_0 + \beta_1 \ln(POil_{t-1}) + \beta_2 \ln(PCorn_{t-1}) + \beta_3 \ln(Grants_{t-1}) + \beta_4 \ln(Grants_{t-2}) + \beta_5 \ln(Output_{t-1}) + \beta_5 POL_1 + \beta_6 POL_2 + \beta_7 K_t + \beta_8 T + \beta_9 T^2) + \xi_t \qquad \ldots\ldots\ldots\ldots \quad (4)$$

where the dependent variable is bio_pat_t and is the count of biofuel-related patents in a particular year t. P_{t-1} is the lagged value of crude oil, $Grants_{t-1}$ and $Grants_{t-2}$ are the lagged federal funding and $Output_{t-1}$ is the total ethanol production in the past year. K_t represents stock of knowledge in year of application 't' of the patent and POL1 and POL2 are dummy variables related to regulatory and financial federal policies in that year. Lastly, T and T2 are the time trend variables whereas ξ_t is the error term and β_0 to β_8 are respective coefficients. We would like to test our hypothesis that all the coefficients are positive and significant.

CHAPTER 5: Methods and Procedures

Most of the induced innovation hypotheses have been tested on renewable technologies (Popp, 2002) as a group or across countries that have policies promoting them (Hu, 2007). This work is first of its kind in testing the induced innovation hypothesis for biofuels and we are faced with insufficient data for some of the variables due to the recent nature of this technology. In this section, we describe the measurement and data sources for our model and present the results of our regression.

Data and Modeling

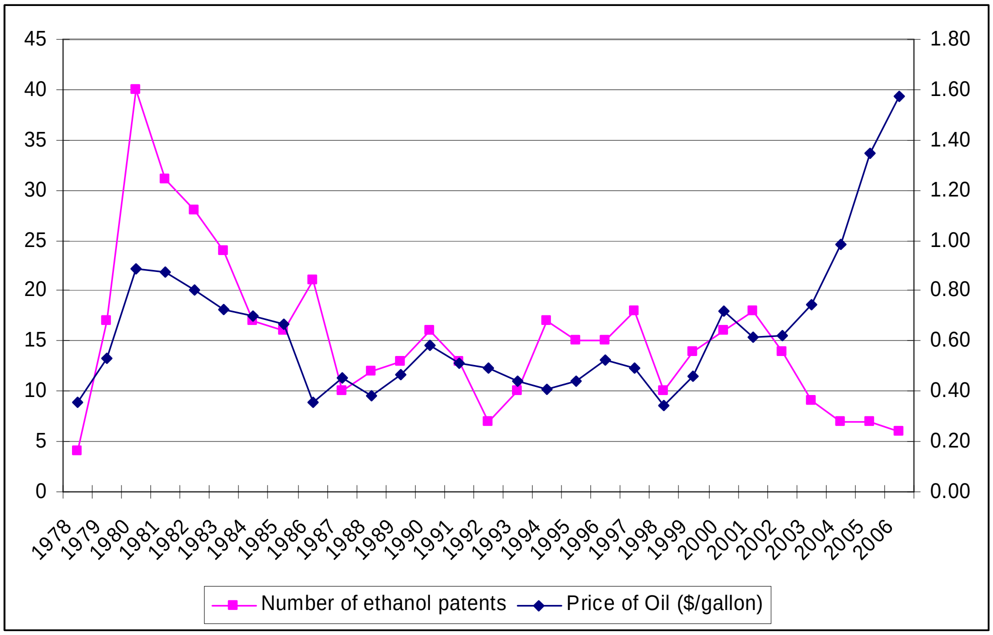
We set out to estimate the time-series model stated in equation (1) for a 27 year period from 1980-2006. Re-stating our count data model,

$$bio\_pat_t = \exp(\beta_0 + \beta_1 \ln(POil_{t-1}) + \beta_2 \ln(PCorn_{t-1}) + \beta_3 \ln(Grants_{t-1}) + \beta_4 \ln(Grants_{t-2}) + \beta_5 \ln(Output_{t-1}) + \beta_5 POL_1 + \beta_6 POL_2 + \beta_7 K_t + \beta_8 T + \beta_9 T^2) + \xi_t \qquad \text{…………} \quad (5)$$

Our dependent variable represents innovation in the ethanol-related technology, which is measured by number of patents in a particular year Patents are an exclusive right issued by national patent offices that allow inventors to use and exploit their inventions for a limited period of time. Patents must meet the criteria of being novel, commercially viable and unobvious to someone skilled in the art (Huffman and Evenson). We begin by finding the number of ethanol-related patents from the US Patent Office (USPTO) based on the patent classification sub-classes for each year, which are provided in the Appendix. . We use the application year of successful patents i.e. patents that have been granted. The primary independent variable is P_t, which is the price of WTI (West Texas

Intermediate) crude oil, the most widely traded in the U.S. crude oil market, in $/gallon. Figure 8 captures the focal relationship between years 1978 and 2006.

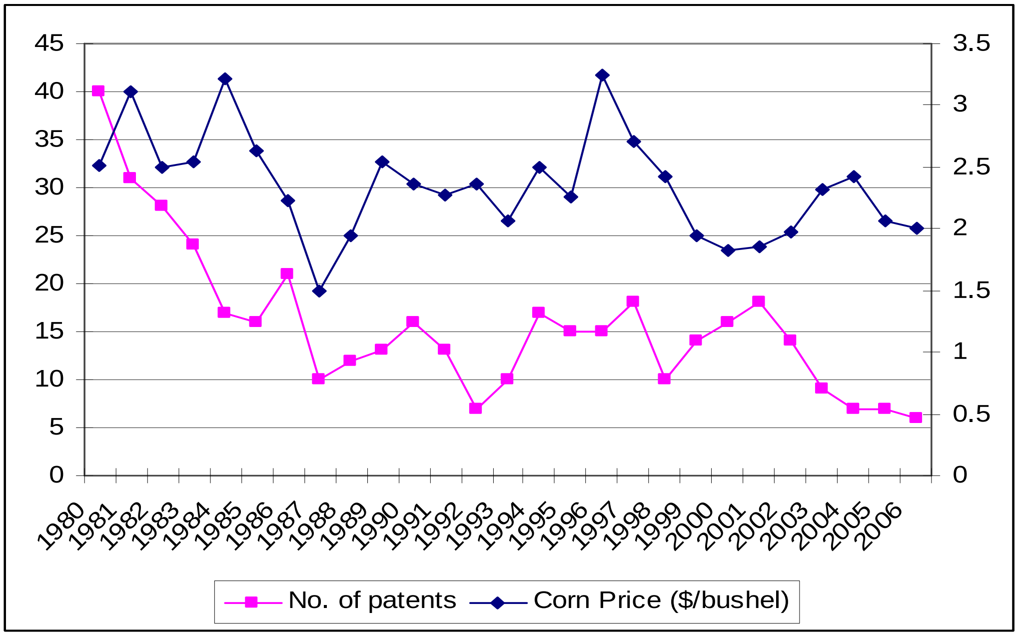
Figure 8: Focal Relationship - Ethanol Patents and Oil Prices from 1978-2006



The rise in oil prices from 1978-80 spawned an increase in patenting activity which peaked in 1980 and then declined with falling prices. The number of patents seems to follow the price trend with a somewhat lagged effect which is expected when time needed for innovation is taken into account. From 2003 however, we see that the patent number curve moves in the opposite direction. This could be due to the fact that we use patent data by application dates of successful patents and have not accounted for patents which have not yet been granted.

The historic data on price of corn is obtained from the National Agricultural Statistics Service (NASS) of the USDA. In Figure 9, we see that there is seems to

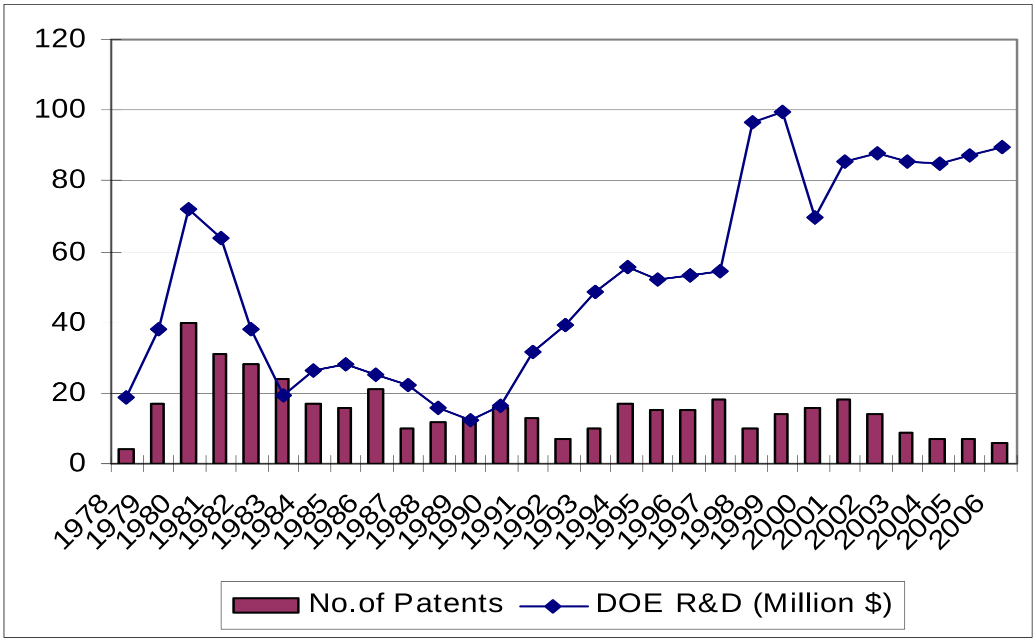
Figure 9: Ethanol Patents and Corn Prices from 1980-2006



be some correlation between corn prices and ethanol patents. In 1987, corn prices were at their lowest resulting in decreased patenting activity whereas rising corn prices in the mid-nineties with record prices around 1997, resulted in new discoveries in more efficient enzymes and processes for cellulosic biomass such as straw, grasses etc.

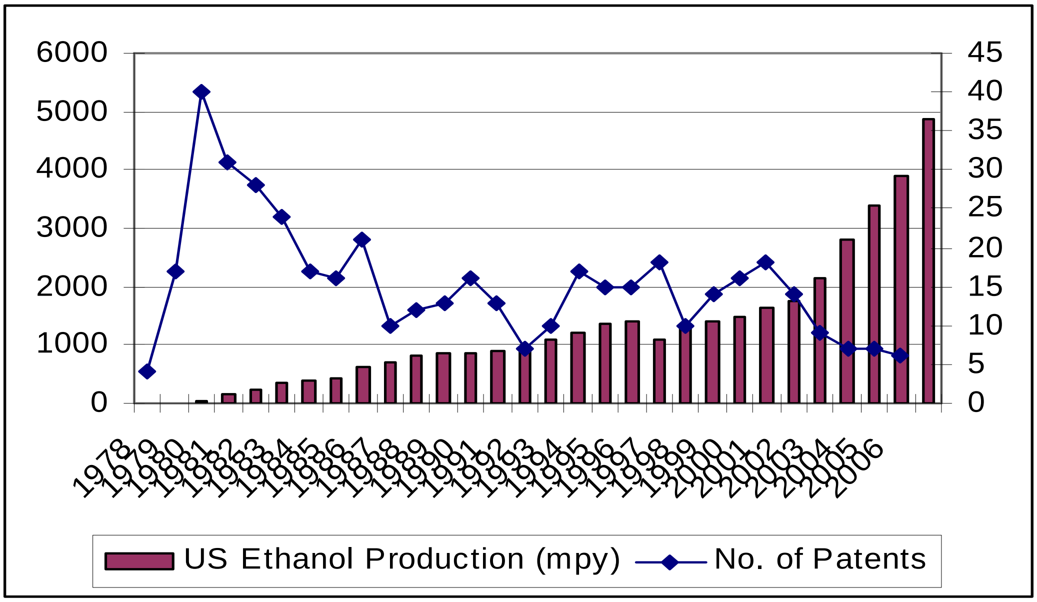
Next, we use DOE funds data towards biofuel RD&D projects from DOE 1999 Budget Appropriations Table and the Kennedy School of Government, Harvard University (Gallagher 2008). Figure 9 depicts the response of innovation to government funded R&D. We find that energy R&D fell dramatically after 1981 when President Reagan took office and federal funds were directed towards long-term projects in basic research and development (Popp 2002). Even though private firms were expected to continue the R&D process, we see decrease in research output, suggesting a strong correlation between federal grants and innovation. From 1991 however, in the Clinton Administration, energy R&D received a boost with grants towards development of alternate fuel vehicles, during which innovations on engine modifications and optimum blend ratios were reported. In 1998, there was another spike in funding which dropped in 2000 and steadily increased until 2006. It is worthwhile to note that this did not have much effect on innovation output as would be expected.

Figure 10: Ethanol Patents and DOE R&D from 1978-2006



The Output data is the total US ethanol production in that year (Brown 2008). We see an interesting trend in Figure 10, between the U.S. ethanol production and patenting activity. It seems to suggest that most of the innovations that were made in the early days of the biofuel industry were towards more efficient production processes. As the industry output increased, the number of patents decreased as there was less motivation for firms to invest in further research. For example, there was reduction in patenting activity by 30% in 1986 even though output increased by 42% from 1984 to 1985.

Figure 11: Ethanol Patents and Ethanol Production from 1978-2006



Next we create separate dummies POL_1 and POL_2 for regulatory and financial federal policies respectively. The regulatory policies include mandates such as the MTBE ban in 2002 and standards such as the RFS set by the Energy Policy Act (EPA) of 2005. The financial policies include incentives such as tax credits such as the ethanol producer tax credit of 51 cents/gallon which has been in effect since 1992. We obtain information on these variables from the IEA database on Global Renewable Energy Policies and Measures.

Popp has measured the existing knowledge stock for future R&D by calculating the probability that the patent granted in a year will be cited by other patents in forthcoming years, thus using the number of citations as an indicator of usefulness of a patent. However, the recent nature of our data set puts limitation on such measures because we see we do not have a good representation of how useful inventions in 2005 would be, since citations are revealed only when a patent is granted. As a result, we cannot measure the existing stock of knowledge K in our model and thus we omit this variable based on the assumption that each patent that is fuel ethanol related will be as important as the others.

Table 2: Description of variables in the model

Variable	Description	Units	Source
bio_pat_t	Number of ethanol-related patents		US Patent Office
$POil_{t-1}$	Price of West Texas Intermediate Crude Oil	$/gallon	Energy Information Agency, Department of Energy
$PCorn_{t-1}$	Price of Corn	$/bushel	NASS, USDA
$Grants_{t-1}$ $Grants_{t-2}$	Federal Funds for ethanol RD&D with a 1 and 2 year lag	millions of dollars	DOE 1999 Budget Appropriations Table and the Kennedy School of Government, Harvard University
$Output_{t-1}$	US Annual Ethanol Production	million gallons/year	Brown, Lester R. “Plan B 3.0: Mobilizing to save the civilization”, Earth Policy Institute, January 2008.
$POL1_t$	Ethanol Production tax credit		Global Renewable Energy Policies and Measures, IEA
$POL2_t$	Renewable Fuel Standard mandate		
T	linear time trend		
T2	quadratic time trend		

Table 2 sums up the description and sources of data for the variables in the model, whereas the summary statistics are given in Table 3.

Table 3: Summary Statistics of Data

Variable	Obs	Mean	Std. Dev	Min	Max
bio_pat_t	27	15.704	7.809	6	40
$POil_{t-1}$	27	-0.545	0.333	-1.071	0.296
$PCorn_{t-1}$	27	0.84	0.178	0.4	1.17
$Grants_{t-1}$	27	3.792	0.618	2.526	4.598
$Grants_{t-2}$	27	3.734	0.624	2.526	4.598
$Output_{t-1}$	27	6.780	0.975	3.689	8.270
$POL1_t$	27	0.556	0.506	0	1
$POL2_t$	27	0.148	0.362	0	1
T	27	14.000	7.937	1	27
T2	27	256.667	228.991	1	729

Next we look at the correlation matrix given in Table 4 which shows the relationships between the different variables in our data. It is interesting to note that there is little correlation between our dependent and primary independent variable $POil_{t-1}$, whereas there seems to be a negative correlation between patenting and ethanol production, implying that the higher the ethanol production in a year, the lower the number of patent applications in that year.

Table 4: Correlation Matrix of Dependent and Independent Variables

	bio_pats	**$POil_{t-1}$**	**$PCorn_{t-1}$**	**$Grants_{t-1}$**	**$Grants_{t-2}$**	**$Output_{t-1}$**	**$POL1_t$**	**$POL2_t$**	**T**	**T2**
bio_pats	1.00									
$POil_{t-1}$	**0.10**	1.00								
$PCorn_{t-1}$	0.39	0.18	1.00							
$Grants_{t-1}$	-0.05	0.31	-0.17	1.00						
$Grants_{t-2}$	-0.16	0.37	-0.16	0.85	1.00					
$Output_{t-1}$	**-0.66**	0.15	-0.37	0.73	**0.74**	1.00				
$POL1_t$	-0.51	-0.06	-0.21	0.71	0.60	**0.86**	1.00			
$POL2_t$	-0.39	0.54	-0.22	0.45	0.45	0.58	0.37	1.00		
T	-0.69	0.08	-0.38	0.62	0.62	0.95	0.86	0.60	1.00	
T2	-0.59	0.26	-0.35	0.71	0.70	0.93	0.81	0.71	0.97	1.00

We see a strong relationship is between the awards of government grants and ethanol production in the subsequent year, suggesting that funds do impact industry output. The tax credit policy and ethanol output are strongly related due to the fact that the policy gives credit incentive of 51 cents per gallon to ethanol producers and this seems to have contributed to increased ethanol production.

Results

We use the Poisson Quasi-Maximum Likelihood Estimation (QMLE) for estimating our count data model. Restating our model in reduced form,

$$E(bio\_pat_t) = \exp(\beta_0 + \beta_1 \ln(POil_{t-1}) + \beta_2 \ln(PCorn_{t-1}) + \beta_3 \ln(Grants_{t-1}) + \beta_4 \ln(Grants_{t-2}) + \beta_5 \ln(Output_{t-1}) + \beta_6 POL_1 + \beta_7 POL_2 + \beta_8 T + \beta_9 T^2) + \xi_t \qquad \ldots\ldots\ldots\ldots \quad (6)$$

We use STATA to estimate the coefficients which are elasticities for each variable and are presented in Table 5 with the Robust Standard Errors in parenthesis. The z-values indicate that all coefficients are significant at the 5% level, except corn price and POL2 which represents the federal mandate policy. Our test for serial correlation comes negative indicating that there is no correlation between the error terms.

Table 5: Poisson QMLE estimates for the bio_patents model

Variable	Coefficient, Robust Std Error	Z-value (95% Conf.Interval)
$POil_{t-1}$	0.358 (0.183)	1.96
$PCorn_{t-1}$	0.3 (0.188)	1.6
$Grants_{t-1}$	1.22 (0.16)	7.51
$Grants_{t-2}$	0.285 (0.10)	2.82
$Output_{t-1}$	-0.857 (0.12)	-7.12
$POL1_t$	-0.778 (0.24)	-3.24
$POL2_t$	0.107 (0.14)	0.76
T	0.307 (0.062)	4.93
T2	-0.008 (0.002)	-5.12
CONSTANT	4.32 (0.58)	7.41

The results indicate that the number of patents is elastic with respect to the main explanatory variable, lagged Oil price, $POil_{t-1}$. This confirms our hypothesis that rising oil prices induces patenting by private firms, which is a measure of innovation. Thus an increase in the price of oil by one percent spawns research activity that results in a 0.358 percent increase in number of patents in the following year. Federal grants also influence patenting as more funds are made available to firms for innovating and we observe that funds in the previous year make a more significant contribution than those lagged by two years. For every one percent increase in government funding, patenting activity will increase by 1.2 percent in the next year and 0.28 percent in the second year.

We observe an interesting effect of the lagged ethanol production variable which contradicts our hypothesis. The Output variable is significant as expected, however it has a negative sign indicating that increased ethanol production discourages firms to invest in R&D. If annual production rises by one percent, then number of patents in the following year will decrease by almost 0.86 percent. Currently all ethanol in the US is from corn and with the government subsidies to encourage more production, there seems to be lesser need for enzymes research to break down alternative feedstock. This would explain the negative effect of ethanol production variable on innovation.

The tax credit policy dummy (POL1) is also negative and significant indicating that the patenting activity decreased by 0.77 during the years the policy was in effect. This could be due to the fact that this credit is mainly given to ethanol producers and hence this variable is highly correlated with ethanol production, leading to similar behavior. The price of corn does not have any effect on patenting activity at the 5% level, which is opposes our hypothesis that with changes in corn prices, firms will be motivated to invest R&D dollars in finding alternate feedstock or more efficient production practices. The dummy on mandate policy (POL2) also contradicts our expectations by being insignificant and therefore seems to have no effect on research activity by firms.

Next we test different combinations of our covariates and find some interesting results. Table 6 gives coefficient values and statistical significance of the various models.

Table 6: Comparison of models

Independent variables	**Coefficients***					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
$POil_{t-1}$	0.36 (1.96)	0.45 (2.47)	0.42 (2.25)	0.3 (1.55)	-0.19 (-0.71)	0.39 (1.59)
$PCorn_{t-1}$	0.3 (1.6)	-	-	-	-	-
$Grants_{t-1}$	1.2 (7.51)	0.32 (2.87)	0.534 (4.46)	0.063 (0.43)	0.23 (1.67)	-
$Grants_{t-2}$	0.28 (2.82)	0.29 (2.64)	-	0.29 (2.12)	0.04 (0.37)	-
$Output_{t-1}$	-0.85 (-7.12)	-0.86 (-6.72)	-0.73 (-4.84)	-0.64 (-5.72)	-	-0.55 (-3.65)
$POL1_t$	-0.78 (-3.24)	-0.67 (-2.69)	-0.67 (-2.05)	-	0.02 (0.1)	0.04 (0.16)
$POL2_t$	0.1 (0.76)	0.09 (0.78)	-0.06 (-0.33)	-	-0.4 (-0.99)	-0.04 -0.2
T	0.3 (4.93)	0.3 (4.62)	0.264 (3.04)	0.14 (2.75)	-0.114 (-2.17)	0.09 (1.29)
T2	-0.008 (-5.12)	-0.008 (-4.92)	-0.007 (-3.31)	-0.004 (-3.08)	0.002 (1.24)	-0.002 (-1.38)

* Z value at 95% confidence interval in parenthesis

When we drop the corn price from our original model, we find that our primary independent variable, POil, becomes more significant. The omission of the 2-year lagged value of federal grants in Model 3 does not have much effect on other variables except the 1 year lagged coefficient which is expected, whereas removing the tax credit dummy, POL1, makes oil price coefficient insignificant at the 5% level. We find a similar trend when we take out ethanol output in Model 5; in fact, all variables except for time trend T become insignificant. In our last model, Model 6, we remove lagged values of federal grants and find that all coefficients but ethanol output are insignificant. Thus, Table 6 indicates that if we were to use statistical significance as the basis for model selection, Model 2 seems a better fit than our original model since corn prices do not contribute as much to ethanol-related patenting activity.

CHAPTER 6: Conclusions and Discussion

In this study, we have attempted to test the role of energy prices in directing technical change in the area of biofuels, specifically, ethanol. We apply the concept of induced innovation using the Innovation Possibility Curve to explain neutral and biased technological innovation in response to factor price changes. For our empirical study, we use patent counts by private biofuel firms to study the impact of oil prices on ethanol technology. We identified the different types of research done by private companies across the ethanol supply chain and found that the highest concentration of research activity is in enzymes technology followed by fuel blend technology and development of efficient distribution networks for ethanol.

The most significant result of our empirical study is the positive impact of oil prices on new innovations in alternative fuels, which is in line with the induced innovation theory. Similar results have been proved in studies mentioned in our literature review, such as Popp (2002) and Wu (2007).

The other determinant of technological change was found to be government research grants and awards, which increase innovation of private firms. After controlling for the role that the price of oil which plays in inducing ethanol-related innovations across a spectrum of technologies such as plant-breeding and enzymes technology, the most effective incentives for biofuels innovations are government research and development grants. In 2006, ethanol manufacturing companies received $93 million in grants and financial awards and a total of $36 million to biotech, genomics and crop management companies combined. These investments clearly stimulated innovation.

However, Popp (2002) finds the opposite trend in his study and he attributes the difficulty in interpreting government R&D to the emphasis of federal grants, which may be on basic research in one time period or marketable technologies in another. In our data, we see that DOE grants after 2002 mainly focused on applied research and feasibility projects, but we do not have details of research emphasis prior to that. In their empirical study of different renewable technologies in the electricity sector, Johnstone et al (2008) found that R&D spending has a negative and significant coefficient for biomass, which they explain as public R&D possibly 'crowding out' private R&D.

We expect that the number of innovations will be higher if the market size is larger. However, increase in annual ethanol production in the past year shows a strong, negative impact on innovation. The government policy of tax credits to ethanol producers may have ramped up ethanol production, but it does not provide incentive to firms to invest more research dollars.

In contrast we find that the tax credit policy that encouraged the amount of ethanol production discouraged innovation in biofuels. Thus while such policies may be justified for national security purposes or for other reasons, they cannot be justified on the basis of stimulating innovation. Our results contradict the findings of Johnstone et al (2008) and Wu (2005) who have shown a positive effect of tax policy on innovation and business R&D spending respectively. One reason could be that Wu and colleagues use business R&D expenditures across nine countries from 1985-1995 as the dependent variable, whereas in our case, it is patenting activity. The Johnstone study looks at biomass such as biogas, renewable municipal waste, liquid biomass etc, used in the process of electricity generation and in contrast with the other renewable sources (wind, ocean etc) biomass responded positively to price-based instruments since it was relatively mature and competitive. In our work, we have looked at biomass solely as a source of transportation fuel.The mandate policy on the other hand is insignificant indicating that imposing the Renewable Fuel Standard (since 2005) of 20% ethanol in gasohol has not affected research outputs along with the ban of MTBE from 2004. One reason for this could be the insufficient number of data points for this dummy (only 5 data points) and we can probably get a better indication of its impact in the coming years. Johnstone et al (2008) in their study of effects of various government policies on various renewable technologies in OECD countries from 1978-2003 found that mandates do not contribute to patenting activity.

Policy Alternatives

This study has clearly demonstrated that federal policy in the form of incentives plays an important role in innovative activity of private firms, whether it is financial grants or subsidies. If we were to look at long-term implications, our data analysis points out that if innovations are a measure of biofuels research, then the focus of federal funds needs to shift to more companies at the lower end of the supply chain, such as biotech firms. Many companies in plant breeding or enzymes technology are smaller privately-held firms such as Ceres Inc or Mendel Technologies which are funded by venture capitalists or NGOs, whereas those in production and distribution are mainly multinational corporations such as Abengoa Bioenergy. From Table 1, we see that about 90% of the patenting activity in the ethanol technology area is done by enzymes research companies. The ethanol industry is at a stage where there is a need for innovations in diverse feedstock in addition to dedicated enzymes to break down different feedstock.

Moreover, there should be incentives such as tax credits, targeted at research in enzymes technology or plant breeding.

There is also a need for better ethanol distribution networks to ensure efficient transportation to refueling stations over a larger geographic area. Ethanol production is expected to be almost 9 billion gallons in 2008, surpassing the 7.2 billion gallon mark that was projected. Thus, the DOE needs to shift focus from production to developing next generation biofuels from cellulosic biomass or synfuels since there is an urgent need to move away from corn-based ethanol, (which accounts for majority of the US ethanol) in the wake of escalating food prices and world hunger.

Limitations

This thesis is a preliminary attempt towards a broader understanding of the ethanol industry and the roles played by energy prices, government policies and private sector investments in determining the direction of innovation in this industry. There are several caveats in our empirical work, the primary being the small size of our data set of 27 observations. We have used private patent counts as a measure of innovation, however, we have not accounted for private sector R&D investments, since we could not obtain data on the latter due to the fact that most companies doing R&D are either privately held or have a diverse R&D portfolio from which it is difficult to separate ethanol related research. From our literature review, we are aware that there is strong correlation between patenting activity of a firm and the dollars it invests in research. Thus, we can expect R&D expenditure to have a positive and significant effect on the number of patents.

Secondly, we had to omit an important variable, 'knowledge stock K' in our regression due to the recent nature of our data, which precluded measurement of this variable. This may have serious implications in our results since the stock of knowledge available to the inventor has been shown to be significant in determining patenting activity (Popp 2002). Whereas we have used one lagged value of primary independent variable, Popp has considered an adaptive expectations model of energy prices, in which expected future prices depend on a weighted average of past prices, which could have given a more accurate representation of the focal relationship. Availability of more data in future will largely overcome these aforementioned shortcomings.

Future Work

Our work has focused on the ethanol industry which uses primarily corn and some first-generation cellulose feedstock such as corn stover and woodchips. However, recently DOE has awarded grants for pilot plants and private sector research in lignocellulosic ethanol made from switchgrass, miscanthus, sugarcane bagasse etc. and next-generation biofuels such as synfuel and biobutanol. Cellulosic biomass is proving to be a better source of ethanol because it is not used as food and has a better net energy balance- producing 36 BTUs for each BTU put in it, as against corn which gives output of 1.3 BTUs per BTU (Krupps 2008). There is also a new wave of interest in the by-products from production process that have commercial value (Waltz 2008). Industrial chemicals (glycerol in biomass production), electricity (bagasse in sugarcane ethanol) and food ingredients (corn starch in corn ethanol) are all potential by-products that can make a cellulosic plant more profitable.

Thus this work can be extended to innovations in second-generation biofuels and the determinants that are driving the research in these areas. As the world addresses global problems such as food shortage and growing population, there will be more skepticism towards using crops for fuel instead of feeding the starved or using land for housing instead of biofuel crops. Already, private sector research is shifting towards second generation biofuels, driven in part by financial incentives from the government, as shown in Table 7.

Table 7: Private Sector Research Projects in 2007

Company	Research Project
Ceres, Inc (CA)	Identify plant genes involved in biosynthesis in switchgrass
Ceres, Inc (CA)	Evaluate herbaceous and woody crops such as switchgrass and willow for ethanol using thermochemical processing
Agrivida, Inc. (MA)	Alter plant compositions for improved biofuel production from rice straw, sorghum and switchgrass
Packer Engineering (IL)	Research and develop on-farm conversion of biomass to synthetic gas
Greenfuels Technologies*, AZ	Algae technology
Amyris Biotechnologies*, CA	Reengineer yeast metabolism to ferment sugarcane into a pure hydrocarbon fuel

Source: Biomass Research and Development Initiative, DOE
* KRUPPS (2008)

However, it is becoming evident that the important task before the research community is to carefully examine the sustainability of the many solutions that are being presented. The uncertainty in oil prices is here to stay and will undoubtedly drive innovations in alternative fuels. The challenge before the government is to adroitly employ policy instruments in order support innovations that would be most sustainable in the long run.

REFERENCES

Ahmad, Syed., (1966). "On the Theory of Induced Innovation", *The Economics Journal*, Vol. 76, No. 302, pp 344-357.

Binswanger, Hans P., Ruttan, Vernon (1978). *Induced Technical Change and Development: Technology, Institutions and Development*, John Hopkins University Press.

BRDI, Biomass Research and Development Initiative, Department of Energy (2007). (http://www.brdisolutions.com)

Brown, Lester R. (2008). *Plan B 3.0: Mobilizing to save the civilization*, Earth Policy Institute, January 2008.

Clark, Kerri et al. (2008). *Lignocellulosic Derived Bioethanol Patent Landscape*, PIPRA, Davis, California.

DOE (1998), Office of Chief Financial Officer, *Budget Authority History Table by Appropriation*, Washington DC.

Gallagher, K. (2008). *DOE Budget Authority for Energy Research, Development, and Demonstration Database*, February 2008.

Griliches, Z., (1957). "Hybrid Corn: An Exploration in the Economics of Technical Change", *Econometrica* 25.

Griliches, Zvi, (1990). "Patent Statistics as Economic Indicators: A Survey". *Journal of Economics Literature*, Volume XXVIII, December 1990, pp 1661-1707.

Hayami, Y., Ruttan, V.W., (1985). *Agricultural Development: An International Perspective*, John Hopkins University Press.

Hayami, Y., Ruttan, V. W., (1970). "Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960", *Journal Of Political Economy* 78 (September-October 1970): 1115-41.

Hicks, J., (1932) *The Theory of Wages*. Macmillan, London.

Hill J. et al. (2006). "Environmental, economic and energetic costs and benefits of biodiesel and ethanol biofuels", *Proceedings of the National Academy of Sciences*, Volume 103(30), July 2006, pp 11206-11210.

Huffman, W. E.and Evenson, R. E. (2006). *Science for Agriculture: A Long Term Perspective*, Blackwell Publishing, Second Edition, 2006.

IEA, International Energy Agency (2007). Global Renewable Energy: Policies and Measures.

Jaffe, A., Newell, R., and Stavins, R. (2001). "Technological Change and the Environment", Resources for the Future, Discussion Paper 00-47REV.

Johnstone N., Hascic, I., Popp, D. (2008). "Renewable Energy Policies and Technological Innovation: Evidence based on Patent Counts", NBER Working Paper 13760.

Krupps, F., Horn, M. (2008). "Earth: The Sequel- The Race to Re-invent Energy and stop Global Warming". Environmental Defense Fund, W.W.Norton and Company, 2008.

Mansfield, E., (1981). "R&D and Innovation: Some Empirical Findings". *R&D Patents and Productivity*, The University of Chicago Press.

Nemet, G., F., Kammen, D., M., (2007). "U.S. energy research and development: Declining investment, increasing need and the feasibility of expansion", *Energy Policy*, Vol 35, 2007, pp 746-755.

Nordhaus, William. "Some skeptical thoughts on the Theory of Induced Innovation", Quarterly *Journal of Economics*, May 1973, 87(2), pp. 208-219.

Pray C. E., Fuglie K., Johnson D. (2007). "Private Agricultural Research", *Handbook of Agricultural Economics*, Volume 3, pp 2607-2640.

Popp, D., (2002). "Induced Innovation and Energy Prices", *The American Economic Review*, Volume 92, No.1, pp 160-180.

RFA Ethanol Industry Outlook, 2007.

Schmookler, J. (1966). *Invention and Economic Growth*. Harvard University Press, Cambridge, MA.

Schumpeter J. (1942). *Capitalism, Socialism and Democracy*, Harper, NewYork.

Sheehan, J., Himmel, M., (1999). "Enzymes, Energy and the Environment: A Strategic Perspective on the U.S. Department of Energy's Research and Development Activities for Bioethanol", *Biotechnology Progress*, Volume 15, No. 5, 1999

Van Gerpen, Jon Harlan, Pruszko, R., Clements, D., Shanks, B., & Knothe, G. (2005). *Building a Successful Biodiesel Business*. Ames, IA: Iowa State University.

Waltz, Emily (2008). "Cellulose ethanol booms despite unproven business models", *Nature Biotechnology*, Volume 26, Number 1, January 2008.

Wooldridge Jeffrey (1997). “Quasi-Likelihood Methods for Count Data”, *Handbook of Applied Econometrics*, Volume 2. M.H. Pesaran and P. Schmidt (eds.), 352-406. Oxford: Blackwell.

Wooldridge Jeffrey (2003). *Introductory Econometrics: A Modern Approach*, 2nd Edition, South-Western College Publishing.

Wu Y., Popp, D., Bretschneider, S. (2007). “The Effects of Innovation Policies on Business R&D: A Cross-National Empirical Study”, *Economics of Innovation and New Technology,* Volume 16(4), June 2007, pp 237-253.

APPENDIX
Methodology for ethanol related patents search

Our aim is to identify U.S appropriate patent classes and sub-classes and within those subclasses, to search for ethanol-specific patents by date of application. Johnstone et al (2008) have used a similar approach in identifying patent applications with the European Patent Office (EPO) in renewable technologies such as wind, solar etc. We present our results of different patent classes and their description in the table below.

Table 1: Ethanol-related patents

US Patent Class Number	Description	Ethanol-related sub-classes	Number of patents
800	Multicellular Living Organisms and unmodified parts thereof and related processes	278/284/288/290	5
435	Chemistry: Molecular Biology and Microbiology	97/99/101/105/161-164/135/202/209/277	400
44	Fuel and Related Compositions	378/388/451	40

Source: United States Patent Office

The first step was use the US Patent Office website to search patent titles containing keywords such as ‘ethanol’. Next, from the patent description we note the current US classification numbers associated with that patent. The third step was to use the class and subclass as keywords to get all patents in that category. As an example, when we searched the patent database for patents with ‘ethanol’ in the patent title, we found many patents in the 435.165 subclass. The description for this class is as follows:

“435.165 - Substrate contains cellulosic material: Processes wherein ethanol is prepared by the biochemical treatment of a cellulose containing material.”

Searching for patents within the 435.165 class for a particular year gives us patents in cellulosic ethanol process in that year. We sum up the patents across all identified classes for a particular year to get our patent count dependent variable in the time-series data.